# Texas Tech University Department of Economics Spring 2018

Eco 4306: Economic and Business Forecasting

## Final Exam

ID:
Short questions (40 points)
Q1. 4 points
Q2. 4 points
Q3. 4 points
Q4. 4 points
Q5. 4 points
Q6. 4 points
<b>Q7.</b> 4 points
Q8. 4 points
Q9. 4 points
<b>Q10.</b> 4 points
Applied problems (64 points)
Q11. 8 points
<b>Q12.</b> 8 points
Q13. 8 points
Q14. 8 points
<b>Q15.</b> 8 points
<b>Q16.</b> 8 points
<b>Q17.</b> 8 points
<b>Q18.</b> 8 points

Name:

## Good luck!

## Question 1. (4 points)

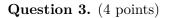
What is Granger causality and how do we test it?

See slide 18 in lec20slides.pdf

## Question 2. (4 points)

Explain what spurious regression problem is and give an example.

See slides 7-9 and 11 in lec 23slides.pdf.



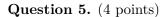
Explain what is means if  $X_t$  and  $Y_t$  are cointegrated. Give an example.

See slide 12 in lec23slides.pdf.

## Question 4. (4 points)

Explain the idea behind error correction model. Draw a diagram illustrating the error correction mechanism.

See slides 22-26 in lec23slides.pdf.



Explain what volatility clustering means.

See slide 9 in lec25slides.pdf.

## Question 6. (4 points)

Explain the difference between moving average (MA) and exponentially weighted moving average (EWMA) models of the conditional variance.

See slide 24, 28 and 31 in lec25slides.pdf.

### Question 7. (4 points)

Write the equation for the autoregressive conditional heteroscedasticity ARCH(1) model. Explain the intuition behind this model.

See slide 6 in lec26slides.pdf.

#### Question 8. (4 points)

What are some weaknesses of ARCH models, and which alternative models have been developed to address them?

See slide 22 in lec26slides.pdf.

#### Question 9. (4 points)

Explain what 1% VaR is and draw a diagram to illustrate this.

See slides 6, 7 and 10 in lec28slides.pdf.

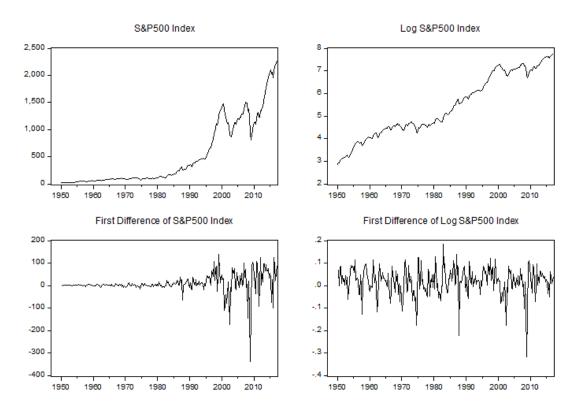
#### Question 10. (4 points)

Consider a GARCH(1,1) model for daily S&P 500 returns from 1/2/1998 to 7/25/2008 sample. With normal innovations, the number of violations  $r_t < r_t^{VaR(0.01)}$  is 42 which represents 1.58% of observations. With innovations from Student-t distribution the number of violations  $r_t < r_t^{VaR(0.01)}$  is 30 or 1.13% of the sample. Which of these two models would be more suitable for risk management purposes and why?

In a large sample, the actual return should be below the 1% VaR threshold in 1% of the sample. With normally distributed innovations, the actual number of days with return below the 1%VaR is 1.58% of the sample so quite a bit more. This is because normal distribution underpredicts how likely extremely low or extremely high realizations can occur. Student-t distribution has fat tails, so these kind of outcomes are more likely to happen, and the actual return is below 1% VaR threshold only 1.13% of times.

#### Question 11 (8 points)

Figure below shows the time series for the S&P500 Index, the log transformed S&P500 Index, and also their first differences. Explain which of the four series are nonstationary, first order weakly stationary, second order weakly stationary.



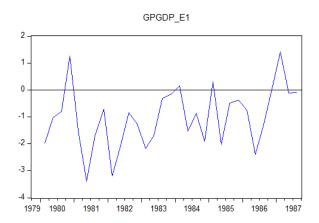
- SP500: it is nonstationary, because it is growing and thus mean is not constant over time
- log og SP500: it is nonstationary, because it is growing and thus mean is not constant over time
- first difference of SP500: it is first order weakly stationary stationary, it fluctuates around a constant mean, but its variance is not constant over time, with larger fluctuations toward the end of the sample
- first difference of log of SP500: it may be first order weakly stationary or second order weakly nonstationary mean does not appear to be growing over time, whether variance is constant over time or not would need to be further tested

#### Question 12 (8 points)

Consider the one quarter ahead Fed's forecast for inflation during the 1979Q4-1987Q3 period.

Suppose that we want to test whether the Fed's forecast are optimal under the symmetric quadratic loss function, which would imply that  $E(y_{t+1}) = f_{t,1}$  and thus the forecast error  $e_{t,1} = y_{t+1} - f_{t,1}$  would have to satisfy  $E(e_{t,1}) = 0$ , and in the regression  $e_{t,1} = \beta_0 + e_t$  coefficient  $\beta_0$  should be zero. Figure below shows that time series plot for the forecast errors, and the results of that regression.

Interpret these results; what can we say about Fed's loss function during 1979Q4-1987Q3 based on them?



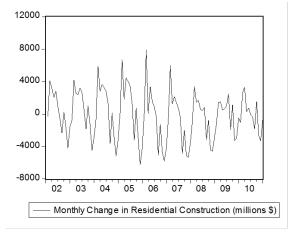
Dependent Variable: GPGDP\_E1 Method: Least Squares Date: 02/19/19 Time: 18:00 Sample (adjusted): 1980Q1 1987Q3 Included observations: 31 after adjustments

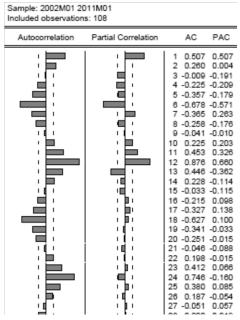
Variable	Coefficient	Std. Error	t-Statistic	Prob.
С	-1.017073	0.202722	-5.017080	0.0000
R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood Durbin-Watson stat	0.000000 0.000000 1.128708 38.21948 -47.23215 1.562466	Mean depend S.D. depende Akaike info cr Schwarz crite Hannan-Quin	ent var iterion rion	-1.017073 1.128708 3.111751 3.158009 3.126830

Based on on the time series plot the forecast error appears to be negative most of the time, thus the inflation forecast  $f_{t,1}$  tends overestimate the true inflation  $y_{t+1}$ . This is confirmed by the negative and statistically significant estimate of  $\beta_0$  in the regression. It suggests that the Fed's loss function is not symmetric quadratic but rather asymmetric, with larger losses associated with underestimating inflation. This makes sense intuitively, since the main goal of Fed in the 1980s was to bring down inflation from double digit levels.

#### Question 13 (8 points)

Consider the data for monthly changes in U.S. residential construction for the period January 2002-January 2011 shown below. Discuss what kind of model would you would estimate for this time series, write its equation, and explain why you would choose this model.





See slide 16 to 20 in lec11slides.pdf.

#### Question 14 (8 points)

Consider two candidate models for change in monthly private residential construction spending, AR(1) and AR(2)+SAR(1), the results for which are below. Evaluate the adequacy of these models based on the correlograms of residuals, AIC and BIC, and statistical significance of coefficients.

Dependent Variable: DCONST Method: ARMA Maximum Likelihood (BFGS) Date: 04/13/19 Time: 10:04 Sample: 1993M02 2013M12 Included observations: 251 Convergence achieved after 3 iterations

Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
С	34.02301	284.5681 0.119560		0.9049
AR(1) SIGMASQ	0.503787 4263658.	0.082472 311155.6	6.108569 13.70266	0.0000
R-squared	0.254386	Mean dependent var		49 44223
Adjusted R-squared	0.248373	S.D. dependent var		2396.078
S.E. of regression Sum squared resid	2077.314 1.07E+09	Akaike info criterion Schwarz criterion		18.12859 18.17072
Log likelihood	-2272.138	Hannan-Quinn criter.		18.14554
F-statistic Prob(F-statistic)	42.30579	Durbin-Watso	n stat	2.030264

Date: 04/13/19 Time: 10:04 Sample: 1993M01 2013M12 Included observations: 251

Q-statistic probabilities adjusted for 1 ARMA term

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
ılı.	l di	1	-0.016	-0.016	0.0654	
· 🗀		2	0.196	0.196	9.8361	0.002
<b>-</b>	<b> </b> -	3	-0.156	-0.156	16.045	0.000
<u> </u>	<b>□</b>  -	4	-0.152	-0.202	21.954	0.000
1 <b>0</b> 1	1 1	5	-0.073	-0.014	23.343	0.000
· ·	<u> </u> '	6	-0.437	-0.430	72.819	0.000
ı <b>₫</b> י	<b>=</b>  -	7	-0.077	-0.174	74.368	0.000
<b>□</b> '	•• -	8	-0.167		81.652	0.000
<b>=</b> '		9	-0.141		86.868	0.000
' <b> </b>	1 10	10		-0.055	94.847	0.000
1   1	ļ <b>!</b> '	11	-0.004		94.852	0.000
'	'	12	0.928	0.873	323.74	0.000
년	! !!	i	-0.022	0.004	323.87	0.000
<u>'</u> _	ļ <b>!</b> '	14		-0.179	333.60	0.000
- □'	'¶'		-0.170		341.37	0.000
<u>"</u> '	']'		-0.138	0.000	346.48	0.000
_'_ '	'!!'			-0.027	347.93	0.000
<u> </u>	'[['		-0.426	0.036	397.29	0.000
<u>"</u>	1 11		-0.074	0.040	398.77	0.000
	1 12	20	-0.181	-0.046	407.75	0.000
<u>q.</u>	ļ <u>.</u> P	21	-0.107	0.110	410.89	0.000
: 🖺	'¶'	22		-0.070	416.75	0.000
	' :	24		-0.017	416.81	0.000
			-0.023	-0.003 0.005	623.42 623.56	0.000
: 🚡	1 11	26		-0.009	633.38	0.000
	1 31		-0.183		642.88	0.000
7:	1 111		-0.103		647.55	0.000
ā;	1 (1)		-0.126		649.09	0.000
	1 16		-0.408	0.052	696.98	0.000
<b>-</b>	1 17		-0.400		698.38	0.000
<b>3</b>			-0.203		710.36	0.000
	1 56		-0.203	0.028	711.77	0.000
i lini		34		-0.001	715.82	0.000
16	1 11	35		-0.014	716.18	0.000
	i d	36		-0.102	897.23	0.000

Dependent Variable: DCONST Method: ARMA Maximum Likelihood (BFGS) Date: 04/13/19 Time: 10:04 Sample: 1993M02 2013M12 Included observations: 251 Convergence achieved after 7 iterations

Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C AR(1) AR(2) SAR(12) SIGMASQ	214.4219 0.497140 0.116143 0.944592 373960.6	1374.109 0.054595 0.052147 0.013249 26485.07	0.156044 9.105947 2.227211 71.29646 14.11968	0.8761 0.0000 0.0268 0.0000 0.0000
R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood F-statistic Prob(F-statistic)	0.934603 0.933540 617.7066 93864109 -1980.137 878.9103 0.000000	Mean depend S.D. depende Akaike info cri Schwarz criter Hannan-Quin Durbin-Watso	nt var iterion rion n criter.	49.44223 2396.078 15.81783 15.88805 15.84609 1.975678

Date: 04/13/19 Time: 10:04 Sample: 1993M01 2013M12 Included observations: 251

Q-statistic probabilities adjusted for 3 ARMA terms

	Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
Ī	r <b>j</b> ir		1	0.011	0.011	0.0322	
	, <b>þ</b> i	<b>    </b>	2	0.054	0.054	0.7743	
	<b>i</b> i[ i	'[  '	3	-0.054	-0.056	1.5282	
	u <b>l</b> i i		4	-0.032	-0.034	1.7972	0.180
	۱ <b>)</b>	<b> </b>	5	0.042	0.049	2.2539	0.324
	<b>-</b>	<b>i</b> d -	6	-0.091	-0.092	4.3953	0.222
	ı <b>⊈</b> ı	d -	7	-0.081	-0.089	6.1091	0.191
	· þa		8	0.112	0.132	9.3965	0.094
	ı <b>d</b> ı	' <b>[</b>   '	9	-0.073	-0.078	10.799	0.095
	- III -	<b> [</b>	10	-0.031	-0.065	11.048	0.137
	u <b>l</b> i			-0.041		11.501	0.175
	1   1			-0.005		11.507	0.243
	1(1)	' <b>[</b>   '		-0.013		11.553	0.316
	1 1			-0.007	0.014	11.565	0.397
	1   1		15	0.006	0.021	11.575	0.480
	1)1	'['	16		-0.024	11.670	0.555
	1 <b>)</b> 11	i  ii	17	0.040	0.045	12.109	0.598
	· <b>[</b> ·	III	18	-0.095		14.580	0.482
	٠ <b>١</b> ٠		19	0.042	0.037	15.068	0.520
	ı <b>j</b> ir	' iii	20	0.070	0.082	16.416	0.495
	u <b>l</b> i	III	21	-0.041		16.875	0.532
	1 11		22		-0.006	16.904	0.596
	1 1		23	-0.005	0.036	16.912	0.659
	· 📮	·	24	0.158	0.146	23.933	0.296
	1   1		25		-0.038	23.952	0.350
	· <b>I</b> I ·	1  1	26			25.527	0.324
	141	'['	27			25.837	0.362
	1 11		28	0.024	0.018	25.999	0.408
	- III -			-0.044		26.564	0.432
	u <b>l</b> i			-0.043		27.097	0.459
	141		31	-0.037		27.498	0.491
	٠ <b>١</b> ٠		32	0.064	0.024	28.673	0.482
	1)1		33	0.022	0.028	28.816	0.527
	1 <b>j</b> i	ļ : <b>j</b> ī:	34	0.044	0.058	29.388	0.549
	1(1			-0.016		29.459	0.596
	· <b>I</b> I ·	<b>□</b> '	36	-0.071	-0.119	30.955	0.569
=							

While coefficients are statistically significant in both AR(1) and AR(2)+S-AR(1) model, both the AIC and the BIC favor AR(2)+S-AR(1) model, and the correlograms of residuals shows that there is a serious problem with seasonality that is not accounted for in the AR(1). Overall, AR(2)+SAR(1) is a much better model for change in monthly private residential construction spending.

#### Question 15 (8 points)

Consider two models for U.S. real GDP, used to construct forecast for the period 2010Q1-2016Q4:

- model A: deterministic trend model for which the sequence of 1-step ahead forecasts has RMSE=103.45 and the multistep forecast has RMSE=1649.06
- model B: stochastic trend model for which the sequence of 1-step ahead forecasts has RMSE=77.32 and the multistep forecast has RMSE=905.18.

The 1-step ahead forecasts are then used to perform the test of equal predictive ability be estimating

$$\Delta L_{t+j,1} = \beta_0 + u_{t+j}$$
 with  $j = 0, 1, 2, \dots, T - t - 1$ 

where  $\Delta L_{t+j,1} = (e_{t+j,1}^A)^2 - (e_{t+j,1}^B)^2$ , and  $e_{t+j,1}^k$  is the one step ahead forecast error for forecast from model k in period t+j. Explain the idea behind this test and interpret its results below. Discuss how we would use it together with above RMSE values in model selection process.

Dependent Variable: DL\_TREND
Method: Least Squares
Date: 04/09/17 Time: 18:34
Sample (adjusted): 2010Q1 2016Q4
Included observations: 28 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
С	5454.311	1293.939	4.215275	0.0002
R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood Durbin-Watson stat	0.000000 0.000000 6846.884 1.27E+09 -286.5045 2.683486	Mean depend S.D. depende Akaike info cri Schwarz criter Hannan-Quin	nt var terion ion	5454.311 6846.884 20.53604 20.58361 20.55058

The main idea behind the test of equal predictive ability is to test whether the difference in MSE or RMSE between two two competing forecasts is statistically significant or not. The null hypothesis of equal predictive ability of forecasts from two models A and B is that the difference in the MSE and RMSE is not statistically significant, and thus the estimated coefficient  $\beta_0$  in the test regression is not statistically significant. If  $\beta_0$  is statistically significant we reject the hypothesis of equal predictive ability of forecasts A and B. This is exactly the case here when comparing model A: a deterministic trend model for real GDP growth vs model B: stochastic trend model since the p-value for  $\beta_0$  is only 0.0002. Model B is thus a much better model for real GDP growth rate forecasting.

#### Question 16. (8 points)

Interpret the results of the Granger causality test for a VAR with two variables:  $y_{1,t} = 400\Delta \log GDP_t$  is the growth rate of the U.S. real GDP and  $y_{2,t} = 400(\Delta \log SP500_t - \Delta \log p_t^{GDP})$  is the inflation adjusted return of S&P 500.

Explain what these Granger causality imply about the usefulness of each of the variables when it comes to predicting the other one. Is there any economic intuition behind these results?

VAR Granger Causality/Block Exogeneity Wald Tests

Date: 04/26/18 Time: 16:57 Sample: 2000Q1 2016Q4 Included observations: 68

Dependent variable: DLRGDP							
Excluded	Chi-sq	df	Prob.				
DLRSP500	6.679366	2	0.0354				
AII	6.679366	2	0.0354				
Dependent vari	Dependent variable: DLRSP500						
Excluded	Chi-sq	df	Prob.				
DLRGDP	1.201515	2	0.5484				
All	1.201515	2	0.5484				

#### The Granger causality tests show that

- we reject the hypothesis that real return of the S&P 500 is not Granger causing real GDP growth rate, since the p-value for the test with  $H_0: \beta_{11} = \beta_{12} = 0$  is 0.0354
- we can not reject the hypothesis that real GDP growth rate is not Granger causing real return of the S&P 500, since the p-value for the test with  $H_0: \alpha_{21} = \alpha_{22} = 0$  is 0.5484

The real returns of the S&P 500 index in the current quarter and the previous quarter are thus useful for predicting next quarter's real GDP growth rate, but real GDP growth in the current quarter and the previous quarter are not useful for predicting next quarter's real return pf the S&P 500 index.

The intuition behind this result is that the financial markets are incorporating news fast, and thus move up or down before the GDP does - they are procyclical but lead the GDP.

#### Question 17. (8 points)

Consider a bivariate VEC

$$\Delta \log p_{t}^{GAS} = \gamma_{1} z_{t-1} + \kappa_{11} \Delta \log p_{t-1}^{GAS} + \kappa_{12} \Delta \log p_{t-2}^{GAS} + \phi_{11} \Delta \log p_{t-1}^{OIL} + \phi_{12} \Delta \log p_{t-2}^{OIL} + \varepsilon_{1,t}$$

$$\Delta \log p_{t}^{OIL} = \gamma_{2} z_{t-1} + \kappa_{21} \Delta \log p_{t-1}^{GAS} + \kappa_{22} \Delta \log p_{t-2}^{GAS} + \phi_{21} \Delta \log p_{t-1}^{OIL} + \phi_{22} \Delta \log p_{t-2}^{OIL} + \varepsilon_{2,t}$$

where  $z_{t-1} = \log p_{t-1}^{GAS} - \beta_1 \log p_{t-1}^{OIL} - \beta_0$  is the error terms period t-1.

Is the coefficient  $\beta_1$  statistically significant? Interpret what the estimated value for  $\beta_1$  means.

Are  $\gamma_1$  and  $\gamma_2$  statistically significant? Are the signs of  $\gamma_1$  and  $\gamma_2$  in the estimated VEC model consistent with error correction mechanism that moves the system back to the long run equilibrium, whenever there is a disruption and  $z_{t-1} \neq 0$ ?

Vector Error Correction Estimates
Date: 05/05/19 Time: 14:53
Sample (adjusted): 1995M04 2010M12
Included observations: 189 after adjustments
Standard errors in () & t-statistics in []

Cointegrating Eq:	CointEq1	
LOG(PGAS(-1))	1.000000	
LOG(POIL(-1))	-0.596465 (0.01477) [-40.3934]	
С	1.582645 (0.05270) [30.0338]	
Error Correction:	D(LOG(PGAS))	D(LOG(POIL))
CointEq1	-0.329559 (0.07388) [-4.46050]	-0.111602 (0.12907) [-0.86464]
D(LOG(PGAS(-1)))	0.354414 (0.09821) [3.60885]	-0.114818 (0.17157) [-0.66924]
D(LOG(PGAS(-2)))	-0.125795 (0.09095) [-1.38320]	-0.027945 (0.15888) [-0.17589]
D(LOG(POIL(-1)))	0.104894 (0.06474) [1.62034]	0.201887 (0.11309) [1.78517]
D(LOG(POIL(-2)))	0.008025 (0.06324) [ 0.12688]	0.079805 (0.11048) [ 0.72232]

The estimated coefficient  $\beta_1 = 0.596$  implies that in the long run a one percent increase in price of oil increases price of gas by 0.596 percent.

The adjustment parameters are  $\gamma_1 = -0.329$  and  $\gamma_2 = -0.111$ . For error correction mechanism to move the system back to the long run equilibrium, whenever there is a disruption and  $z_{t-1} \neq 0$  the adjustment parameters need to satisfy  $\gamma_1 \leq 0$ ,  $\gamma_2 \geq 0$  and they can not be both equal zero at the same time. In the estimated VEC  $\gamma_1$  is consistent with the error correction mechanism since it's negative, while  $\gamma_2$  is not consistent with the error correction mechanism because it's negative. But only  $\gamma_1$  is statistically significant,  $\gamma_2$  is not. It thus makes sense to restrict the model and impose  $\gamma_2 = 0$  which will make model consistent with the error correction mechanism that moves the system back to the long run equilibrium, whenever there is a disruption and  $z_{t-1} \neq 0$ .

#### Question 18. (8 points)

Consider the GARCH(1,1) model for the S&P 500 daily returns.

Dependent Variable: R							
Method: ML - ARCH (BHHH) - Normal distribution							
Sample: 5815 8471							
Included observations:	2657						
Convergence achieved	after 10 iterati	ons					
Bollerslev-Wooldrige r	obust standard	l errors & cova	riance				
Variance backcast: ON							
GARCH = C(2) + C(3)	*RESID(-1)^:	2 + C(4)*GAR	CH(-1)				
Coefficient Std. Error z-Statistic Prob.							
C	C 0.036267 0.017439 2.079665 0.0376						
	Variance	Equation :					
C	0.010421	0.005245	1.987099	0.0469			
RESID(-1)^2	0.065649	0.011338	5.790038	0.0000			
GARCH(-1)	0.927400	0.011045	83.96233	0.0000			
R-squared	-0.000534	Mean depend	ent var	0.009761			
Adjusted R-squared -0.001666 S.D. dependent var 1.146761							
S.E. of regression 1.147716 Akaike info criterion 2.888638							
Sum squared resid 3494.671 Schwarz criterion 2.897498							
Log likelihood	-3833.556	Durbin-Watso	on stat	2.079139			

Write the equations for the estimated GARCH(1,1) model, with estimated parameter values plugged into these equations.

On April 2, 2008, the 1-day-ahead conditional mean is  $\mu_{t|t-1} = 0.036$ , the 1-day-ahead conditional standard deviation  $\sigma_{t|t-1} = 1.785$ . Calculate the 1% VaR and 5% VaR, given that  $\Phi^{-1}(0.05) = -1.645$  and  $\Phi^{-1}(0.01) = -2.326$ . Interpret these numbers, given a portfolio worth 1 million dollars.

The estimated GARCH(1,1) model is

$$\begin{aligned} r_t &= 0.036 + \varepsilon_t \\ \varepsilon_t &= \sigma_{t|t-1} z_t \qquad z_t \sim N(0,1) \\ \sigma_{t|t-1}^2 &= 0.010 + 0.065 \varepsilon_{t-1}^2 + 0.927 \sigma_{t-1|t-2}^2 \end{aligned}$$

With normally distributed innovastions, the 1% VaR and 5% VaR are calculated as

$$r_t^{VaR(0.01)} = \mu_{t|t-1} - 2.326\sigma_{t|t-1}$$

and

$$r_t^{VaR(0.05)} = \mu_{t|t-1} - 1.645\sigma_{t|t-1}$$

Thus, the 1% VaR is  $0.036-2.326\times1.785=-4.117\%$  and the 5% VaR is  $0.036-1.645\times1.785=-2.900\%$ . This means that if on April 1, we have a portfolio worth 1 million dollars, there is 1% chance that we could lose at least \$41,170 on April 2 and 1% chance that we could lose at least \$29,000.