

MGMT 237E:
Empirical Methods in Finance
Homework 3

Yi-Chi Chan Zhaofang Shi
Ahswini Kumar Ashok Kumar George Bonebright

January 26, 2016

1.1. $y_t = \phi_0 + \phi_2 y_{t-2} + \epsilon_t$
 $\mu = \phi_0 + \phi_2 \mu$
 $y_t - \mu = \phi_2 (y_{t-2} - \mu) + \epsilon_t$
 $(y_t - \mu)(y_{t-1} - \mu) = \phi_2 (y_{t-2} - \mu)(y_{t-1} - \mu) + \epsilon_t (y_{t-1} - \mu)$
 $\gamma_1 = \phi_2 \gamma_1, |\phi_2| < 1$
First order auto-covariance: $\gamma_1 = 0$

$$\mu = \frac{\phi_0}{1-\phi_2}$$

$$\gamma_0 = \phi_2 \gamma_2 + \sigma^2$$

$$\gamma_2 = \phi_2 \gamma_0$$

$$\gamma_0 = \frac{\sigma^2}{1-\phi_2^2}$$

Second order auto-covariance: $\gamma_2 = \phi_2 \frac{\sigma^2}{1-\phi_2^2}$

1.2. $\phi_{pp} = \text{corr}(y_t, y_{t-p} | y_{t-p}, y_{t-p+1}, y_{t-p+2}, \dots, y_{t-1})$
 $\phi_{11} = \text{corr}(y_t, y_{t-1} | y_{t-1}) = \text{corr}(\phi_0 + \phi_2 y_{t-2} + \epsilon_t, y_{t-1} | y_{t-1})$
 $= \text{corr}(\phi_0, y_{t-1} | y_{t-1}) + \text{corr}(\phi_2 y_{t-2}, y_{t-1} | y_{t-1}) + \text{corr}(\epsilon_t, y_{t-1} | y_{t-1})$
 $= 0$

$$\phi_{22} = \text{corr}(y_t, y_{t-2} | y_{t-2}, y_{t-1}) = \text{corr}(\phi_0 + \phi_2 y_{t-2} + \epsilon_t, y_{t-2} | y_{t-2}, y_{t-1})$$

$$= \text{corr}(\phi_0, y_{t-2} | y_{t-2}) + \text{corr}(\phi_2 y_{t-2}, y_{t-2} | y_{t-2}) + \text{corr}(\epsilon_t, y_{t-2} | y_{t-2})$$

$$= \phi_2$$

1.3. $y_t = \phi_0 + \phi_2 y_{t-2} + \epsilon_t$
 $= \phi_0 + \phi_2 (\phi_0 + \phi_2 y_{t-4} + \epsilon_{t-2}) + \epsilon_t$
 $= \phi_0 (1 + \phi_2) + \phi_2^2 y_{t-4} + \phi_2 \epsilon_{t-2} + \epsilon_t$
 $= \phi_0 (1 + \phi_2) + \phi_2^2 (\phi_0 + \phi_2 y_{t-6} + \epsilon_{t-4}) + \phi_2 \epsilon_{t-2} + \epsilon_t$
 $= \phi_0 (1 + \phi_2 + \phi_2^2) + \phi_2^3 y_{t-6} + \phi_2^2 \epsilon_{t-4} + \phi_2 \epsilon_{t-2} + \epsilon_t$
 $= \phi_0 (1 + \phi_2 + \phi_2^2 + \dots + \phi_2^{k-1} + \phi_2^k) + \phi_2^{k+1} y_{t-2k-2} + \phi_2^k \epsilon_{t-2k} + \dots + \phi_2^2 \epsilon_{t-4} +$
 $\phi_2 \epsilon_{t-2} + \epsilon_t$
 $\psi_{2k} = \frac{\delta y_t}{\epsilon_{t-2k}} = \phi_2^k$
 $\psi_{2k-1} = \frac{\delta y_t}{\epsilon_{t-2k+1}} = 0$
 $\psi_k = \frac{\phi_2^{\frac{k}{2}}}{2} + (-1)^k \frac{\phi_2^{\frac{k}{2}}}{2}$

1.4. $\hat{r}_t(h) = \mu + \psi_h \epsilon_t + \psi_{h+1} \epsilon_{t-1} + \dots$
 $= \frac{\phi_0}{1-\phi_2} + (\frac{\phi_2^{\frac{h}{2}}}{2} + (-1)^h \frac{\phi_2^{\frac{h}{2}}}{2}) \epsilon_t + (\frac{\phi_2^{\frac{h+1}{2}}}{2} + (-1)^{(h+1)} \frac{\phi_2^{\frac{h+1}{2}}}{2}) \epsilon_{t-1} + \dots$
 $v_t(h) = \epsilon_{t+h} + \psi_1 \epsilon_{t+h-1} + \psi_2 \epsilon_{t+h-2} + \dots + \psi_{h-1} \epsilon_{t+1}$
 $= \epsilon_{t+h} + \phi_2 \epsilon_{t+h-2} + \phi_2^2 \epsilon_{t+h-4} + \dots + (\frac{\phi_2^{\frac{h-1}{2}}}{2} + (-1)^{(h-1)} \frac{\phi_2^{\frac{h-1}{2}}}{2}) \epsilon_{t+1}$

$$\begin{aligned}
Var[v_t(h)] &= (1 + \psi_1^2 + \psi_2^2 + \dots + \psi_{h-1}^2) \sigma_\epsilon^2 \\
&= (1 + \phi_2^2 + \phi_4^2 + (\frac{\phi_2^2}{2} + (-1)^{(h-1)} \frac{\phi_2^2}{2})^2) \sigma_\epsilon^2
\end{aligned}$$

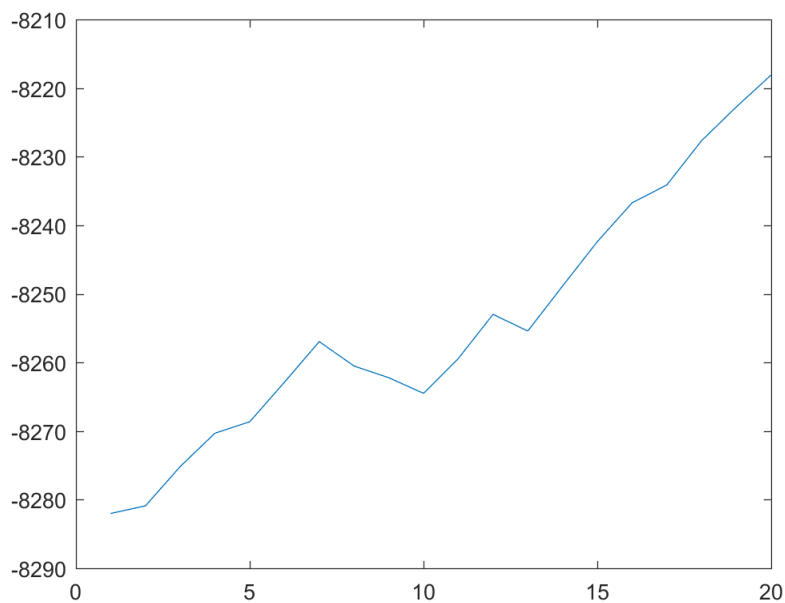
3.1. The best model for the data is the AR(1) model. Although higher order lags do have some auto-correlation, it is most likely due to carry over from the first lag.

ARIMA(20,0,0) Model:

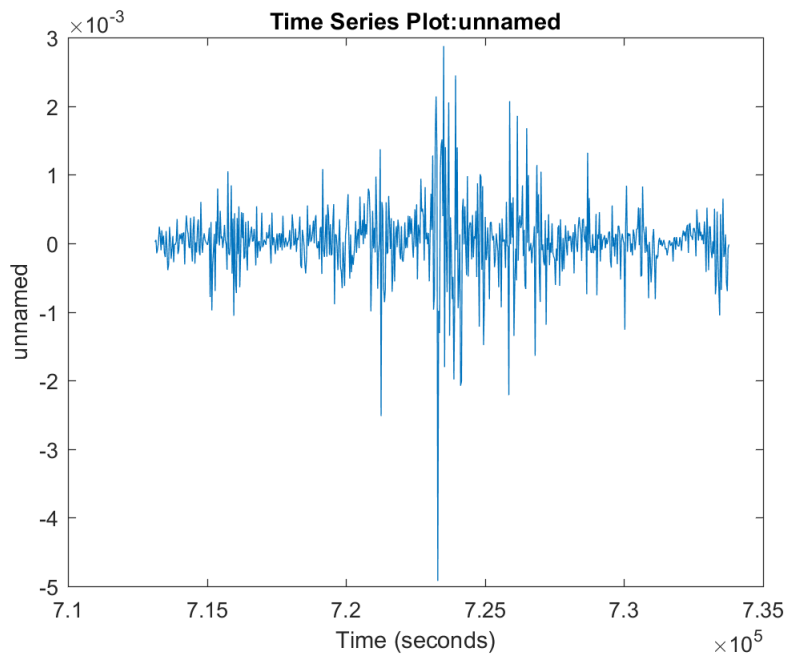
Conditional Probability Distribution: Gaussian

| Parameter | Value | Standard Error | t Statistic |
|-----------|-------------|-------------------|----------------|
| Constant | 0.000106277 | 5.88213e-05 | 1.80678 |
| AR{1} | 0.879565 | 0.025217 | 34.8798 |
| AR{2} | 0.0743894 | 0.0344552 | 2.15901 |
| AR{3} | -0.0597999 | 0.041664 | -1.43529 |
| AR{4} | -0.0148535 | 0.0394274 | -0.376731 |
| AR{5} | 0.0889085 | 0.0324679 | 2.73835 |
| AR{6} | 0.0399696 | 0.0371973 | 1.07453 |
| AR{7} | -0.144663 | 0.0422749 | -3.42195 |
| AR{8} | 0.231795 | 0.0379251 | 6.11192 |
| AR{9} | 0.00882295 | 0.044628 | 0.1977 |
| AR{10} | -0.180959 | 0.0352317 | -5.13626 |
| AR{11} | 0.0730484 | 0.0445958 | 1.63801 |
| AR{12} | 0.0988266 | 0.0452402 | 2.18449 |
| AR{13} | -0.116297 | 0.0401625 | -2.89565 |
| AR{14} | -0.0083523 | 0.0357916 | -0.233359 |
| AR{15} | -0.0149868 | 0.0425696 | -0.352055 |
| AR{16} | 0.0993057 | 0.0532711 | 1.86416 |
| AR{17} | -0.0829113 | 0.0563352 | -1.47175 |
| AR{18} | 0.0560752 | 0.0557955 | 1.00501 |
| AR{19} | -0.00384941 | 0.0437847 | -0.0879167 |
| AR{20} | -0.0516555 | 0.0287052 | -1.79952 |
| Variance | 2.65011e-07 | 9.73801e-08 | 2.72141 |

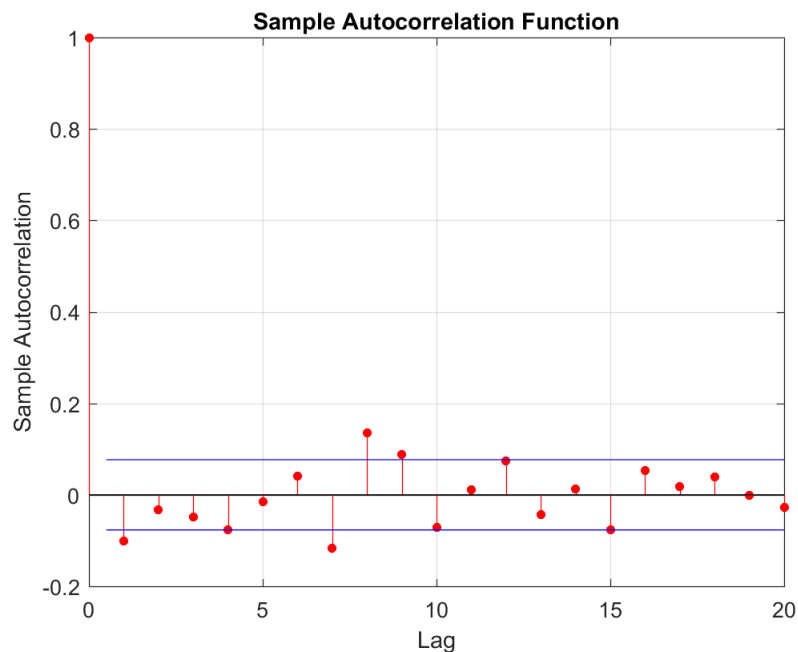
Graph of BIC values:



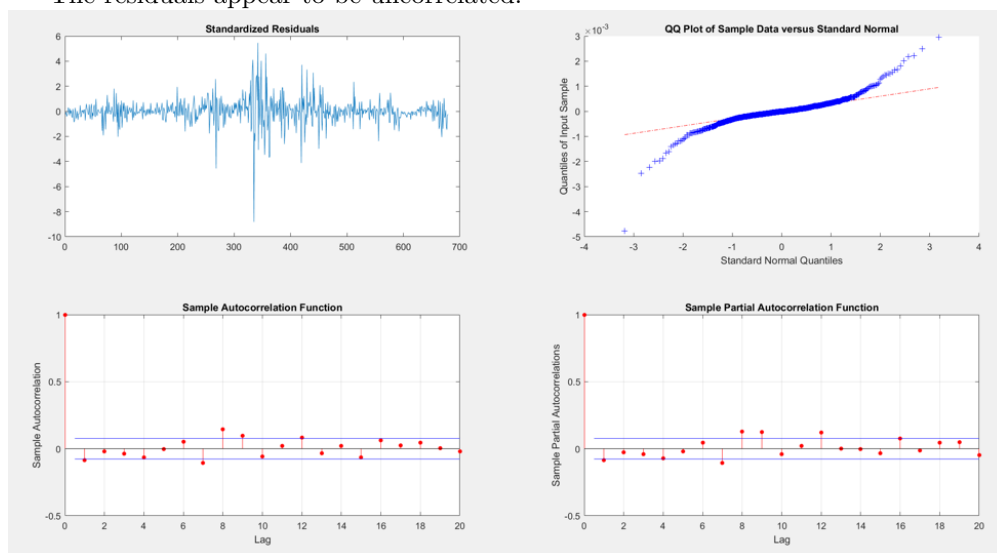
Graph of Time Series:



Graph of Autocorrelation Function:

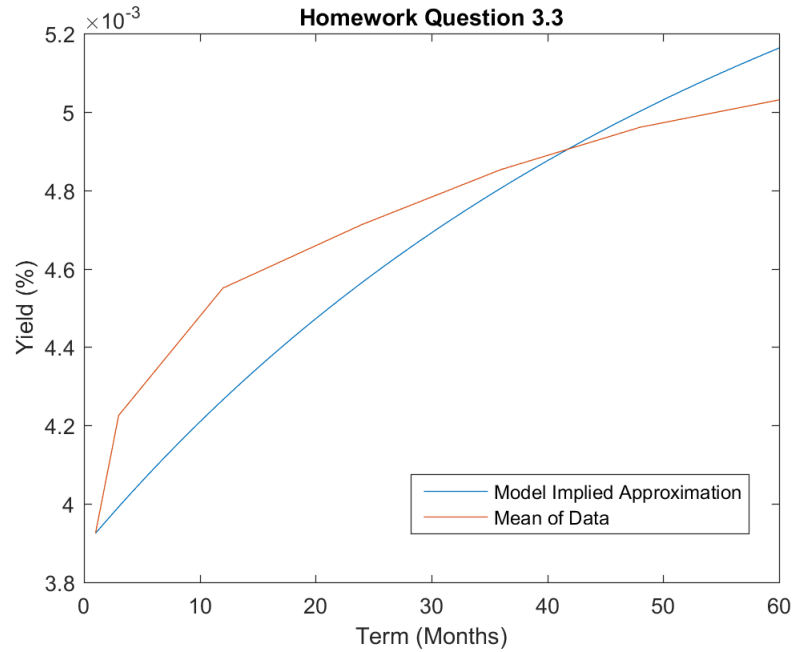


3.2. For AR(1) Estimate: $\mu = .0039$; $\phi = .9725$; $\sigma = 5.46 * 10^{-4}$
The residuals appear to be uncorrelated:



The model does not capture new information such as policy changes which are independent of past monthly yields. Furthermore, the AR(1) model assumes stationarity so variation over past periods is not captured.

3.3. Comparison of Model and Actual Data:



Although the model does not appear to be a good fit for the data it isn't an unusable estimate. The model seems to capture an average of the slopes of the unconditional means of interest rates. Additionally, the Vasicek model is based on a single factor which prevents it from capturing the curvature of a multi-factor function.

```

1 clear all
2 %% Problem 3: AR(1) model of the yield curve
3 %% (1). estimate different AR(p) models for the 1-month yield
4 data = xlsread('fama_bliss_data.xlsx');
5 for i =1:length(data(:,1))
6     data(i, 1) = datenum(num2str(data(i,1)), 'yyyymmdd');
7 end
8 dropped_data = data(1:(751-72), :);
9 y = dropped_data(:,2);
10
11 p=20;
12 aic=zeros(p,1);
13 bic=zeros(p,1);
14 for i =1:p
15     Mdl=arima(i,0,0);
16     [EstMdl,EstParamCov,logL,info] = estimate(Mdl,y);
17     [aic(i,1), bic(i,1)]=aicbic(logL,i,679);
18 end
19 plot(bic)
20 % I choose AR(1) model because the BIC value is the lowest.
21 ToEstMdl = arima(1, 0, 0);
22 ToEstMdl.Constant = 0;
23 Y = dropped_data(:, 2);
24 [EstMdl, EstParamCov, logL, info] = estimate(ToEstMdl, Y);
25 OurModel = arima('AR',{0.992729},'Variance',0.2,'Constant',0);
26 [E,V] = infer(OurModel,Y);
27
28 ts1 = timeseries(E, dropped_data(:, 1));
29 plot(ts1)
30 datetick('x','mmm yyyy')
31 autocorr(E)
32 %%
33 %% (2). Estimate an AR(1) model on monthly data for the 1-month
    yield
34 Y = dropped_data(:,2);
35 X = zeros(length(Y), 3);
36 X(:, 1) = 1;
37 X(:, 2) = lagmatrix(Y,1);
38 [parameters, bint, residuals,rint,stats] = regress(Y,X);
39 mu = parameters(1)/(1-parameters(2));
40 phi = parameters(2);
41 sigma = sqrt(var(residuals, 'omitnan'));
42 %%
43 %% (3). calibrate the Vasicek model to get the best ?t for the
    average yield curve in the sample
44 largest = 60;
45 a_bar = zeros;
46 b_bar = zeros;
47 a_bar(1) = 0;
48 b_bar(1) = -1;
49 delta0 = 0;
50 delta1 = 1;
51 % initial guess for lamda_0 and lamda_1 from class notes
52 lamda_0 = -0.1144;
53 lamda_1 = -10.741;
54 step = 0.1;
55 step-size = 100;

```



```

56 l0 = lamda_0-step*step_size:step:lamda_0+ step*step_size;
57 l1 = lamda_1-step*step_size:step:lamda_1+step*step_size;
58 minsum = 1000;
59 l0min = 0;
60 l1min = 0;
61 Vasicek_Y = zeros;
62 Vasicek_Y(1) = mean(Y);
63
64
65 for lambda0 = l0
66     for lambda1 = l1
67         for i =2:largest
68             b_bar(i) = b_bar(i-1)*(phi - sigma*lambda1) - delta1;
69             a_bar(i) = a_bar(i-1) - delta0 + b_bar(i-1)*((1-phi)*mu
- sigma*lambda0) + 1/2*sigma^2*(b_bar(i-1))^2;
70         end
71         g = Y;
72         z = zeros(length(Y),6);
73         k = 1;
74         for i = [3,12,24,36,48,60]
75             z(:,k) = -(a_bar(i)+b_bar(i)*g)/i;
76             k = k+1;
77         end
78         if sum((mean(dropped_data(:,2:8))-mean([g,z]))'.^2) <
minsum
79             minsum = sum((mean(dropped_data(:,2:8))-mean([g,z]))'.
^2);
80             l0min = lambda0;
81             l1min = lambda1;
82         end
83     end
84 end
85
86 %Using the l0min and l1min
87 for i =2:largest
88     b_bar(i) = b_bar(i-1)*(phi - sigma*l1min) - delta1;
89     a_bar(i) = a_bar(i-1) - delta0 + b_bar(i-1)*((1-phi)*mu -
sigma*l0min) + 1/2*sigma^2*(b_bar(i-1))^2;
90 end
91
92 for i =2:largest
93     Vasicek_Y(i) = -1/i*a_bar(i) -1/i*b_bar(i)*Vasicek_Y(1);
94 end
95 periods = [1 3 12 24 36 48 60];
96 TermStructure = zeros;
97 for i=1:length(periods)
98     TermStructure(i) = mean(dropped_data(:, i+1));
99 end
100 x = 1:60;
101 plot(x, Vasicek_Y, periods, TermStructure);
102 %%

```