

# 程序代写代做 CS编程辅导



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University of New South Wales, School of Economics

## Financial Econometrics

### Tutorial 4 solutions



#### 1. Estimating MA

Consider an invertible MA(1) process:  $y_t = \mu + \varepsilon_t + \theta_1 \varepsilon_{t-1}$ ,  $\varepsilon_t \sim iid WN(0, \sigma^2)$ .

Using the MA(1) equation, we find

$$\varepsilon_1 = y_1 - \mu - \theta_1 \varepsilon_0,$$

$$\varepsilon_2 = y_2 - \mu - \theta_1 \varepsilon_1 = y_2 - \mu - \theta_1 (y_1 - \mu - \theta_1 \varepsilon_0),$$

$$\varepsilon_3 = y_3 - \mu - \theta_1 \varepsilon_2 = y_3 - \mu - \theta_1 [y_2 - \mu - \theta_1 (y_1 - \mu - \theta_1 \varepsilon_0)],$$

which are *non-linear* functions of the parameters  $(\mu, \theta_1)$ . Obviously, the same can be done for  $t = 4, 5, \dots$ . The shock  $\varepsilon_t$  is interpreted as the 1-step ahead forecast error. Hence, the “least squares” principle here is to choose the values of  $(\mu, \theta_1)$  to minimise the sum of squared 1-step ahead forecast errors:  $SSE(\mu, \theta_1) = \varepsilon_1^2 + \varepsilon_2^2 + \varepsilon_3^2$ . Note that the SSE is a *non-linear* function of  $(\mu, \theta_1)$  and its minimisation is carried out by numerical search algorithms in practice. For a long series of  $y_t$ , say  $T = 1000$ , the above applies straightforwardly. We note that the expression of  $\varepsilon_3$  involves the term  $\theta_1^3 \varepsilon_0$ . In general, the expression of  $\varepsilon_t$  involves the term  $\theta_1^t \varepsilon_0$ . For large  $T$ , whether or not  $\varepsilon_0$  is known is unimportant, because the term  $\theta_1^t \varepsilon_0$  converges to zero quickly as  $t$  increases as long as the MA is invertible (where  $|\theta_1| < 1$ ). However that, when the MA(1) is not invertible (implies  $|\theta_1| \geq 1$ ), the term  $\theta_1^t \varepsilon_0$  cannot be ignored.

**MLE** is based on maximizing the likelihood of observing  $y_t$ . An important technical caveat here: the probability to observe the exact values  $y_t$  is zero (separately or jointly) because we deal with continuous random variable. The likelihood is proportional to the joint probability that in each time the random variable will fall within the range  $y_t \pm \delta$ , where  $\delta$  is a very (infinitesimally) small positive number, the joint probability is

$$P(y_1 - \delta < Y_1 < y_1 + \delta \text{ and } y_2 - \delta < Y_2 < y_2 + \delta \text{ and } \dots y_T - \delta < Y_T < y_T + \delta) = CDF(y_1 + \delta, y_2 + \delta, \dots, y_T + \delta) - CDF(y_1 - \delta, y_2 - \delta, \dots, y_T - \delta)$$

The same small  $\delta$  is used in the definition of the derivative:

$$\lim_{\delta \rightarrow 0} \frac{CDF(y_1 + \delta, y_2 + \delta, \dots, y_T + \delta) - CDF(y_1 - \delta, y_2 - \delta, \dots, y_T - \delta)}{2\delta} = f(y_1, y_2, \dots, y_T),$$

where  $f(y_1, y_2, \dots, y_T)$  is the pdf, derivative of the CDF

Hence for small positive  $\delta$ :

$$P(y_1 - \delta < Y_1 < y_1 + \delta, \dots, y_T - \delta < Y_T < y_T + \delta) \approx 2\delta f(y_1, y_2, \dots, y_T)$$

Therefore, maximizing  $P$  is equivalent to maximizing  $f(\cdot)$  because  $\delta > 0$ .

Obviously you do not need to derive the part above, but hopefully it helps with understanding. So, in order to maximise the probability that any random sample

(a collection of random variables) falls as close as possible to the observed realization of the random sample by choosing the parameters which characterise the specific family of distributions (we typically use Normal with just two parameters). The parameters of the distribution are related to the parameters of the model for a given model. If there is no such relation the parameters of the model are not identified.

Coming back from this illuminating digression the joint pdf is given by  $f(y_3, y_2, y_1)$ . We can factorise it:

$$f(y_3, y_2, y_1) = f(y_3, y_2 | \Omega_1) f(y_1) = f(y_3 | \Omega_2) f(y_2 | \Omega_1) f(y_1)$$

Note: that  $f$  is positive: it can be zero in regions where the random variable does not have a support, but this is not the case for normal distribution; \*[more exotically  $f$  may be allowed to turn negative as an explanation for *negative energy* and *dark matter*, but we will leave all the fun with this to physicists]. Natural log  $\ln$  transformation can be used for simplicity because  $\ln$  is an increasing function. Namely, maximizing  $f(y_3, y_2, y_1)$  is equivalent to maximizing  $\ln f(y_3, y_2, y_1)$ .

So  $y_t = \mu + \varepsilon_t + \theta_1 \varepsilon_{t-1}$  and  $\varepsilon_t \sim iid WN N(0, \sigma^2)$ . Hence

The conditional (and unconditional) distribution of  $y_t$  is Normal because  $y_t$  is just a linear combination of  $\varepsilon_t, \varepsilon_{t-1}$  which are Normally distributed by assumption. Find the mean and the variance of  $y_t$ -s and write down the pdfs.

$$y_1 \sim N(\mu, (1 + \theta_1^2)\sigma^2); f(y_1) = (2\pi(1 + \theta_1^2)\sigma^2)^{-1/2} \exp\left\{-\frac{(y_1 - \mu)^2}{2(1 + \theta_1^2)\sigma^2}\right\}$$

$$y_2 | \Omega_1 \sim N(\mu + \theta_1 \varepsilon_1, \sigma^2); f(y_2 | \Omega_1) = (2\pi\sigma^2)^{-1/2} \exp\left\{-\frac{(y_2 - \mu - \theta_1 \varepsilon_1)^2}{2\sigma^2}\right\}$$

$$y_3 | \Omega_2 \sim N(\mu + \theta_1 \varepsilon_2, \sigma^2); f(y_3 | \Omega_2) = (2\pi\sigma^2)^{-1/2} \exp\left\{-\frac{(y_3 - \mu - \theta_1 \varepsilon_2)^2}{2\sigma^2}\right\}$$

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Note that when computing  $y_1$  we treated  $\varepsilon_0$  as a random variable. In fact this causes a

problem, because when we move one period from  $t=1$  ahead we cannot distinguish between  $\varepsilon_0$  and  $\varepsilon_1$  (each of them is only identified from the data). Therefore it is

important to condition on  $\varepsilon_0$  \* [it can be integrated out of the likelihood if we want to assume joint normality of  $\varepsilon_0$ , but the integration is not simple].

So, we will maximize  $\ln f(y_1|\varepsilon_0)$  and

$$y_1|\varepsilon_0 \sim N(\mu + \theta_1 \varepsilon_0, \sigma^2); f(y_1|\varepsilon_0) = (2\pi\sigma^2)^{-1/2} \exp\left\{-\frac{(y_1 - \mu - \theta_1 \varepsilon_0)^2}{2\sigma^2}\right\}$$

Now as we move forward  $\varepsilon_1$  can be identified. In fact, we can rewrite all three densities as:

$$\begin{aligned} \ln f(y_3, y_2, y_1|\varepsilon_0) &= \ln[f(y_3|y_2, y_1, \varepsilon_0)f(y_2|y_1, \varepsilon_0)f(y_1|\varepsilon_0)] \\ &= \ln f(y_3|y_2, y_1, \varepsilon_0) + \ln f(y_2|y_1, \varepsilon_0) + \ln f(y_1|\varepsilon_0) \\ &= 3 \ln \left[ (2\pi\sigma^2)^{-\frac{1}{2}} \right] \\ &\quad - \frac{1}{2\sigma^2} \left( (y_1 - \mu - \theta_1 \varepsilon_0)^2 + (y_2 - \mu - \theta_1 \varepsilon_1)^2 + (y_3 - \mu - \theta_1 \varepsilon_2)^2 \right) \\ &= 3 \ln (2\pi\sigma^2)^{-\frac{1}{2}} - \frac{1}{2\sigma^2} (\varepsilon_1^2 + \varepsilon_2^2 + \varepsilon_3^2) \end{aligned}$$

Note that in this case in  $f(y_2|y_1, \varepsilon_0)$  we do not have to condition on  $\varepsilon_1$ , it can be discovered if we know  $y_1, \varepsilon_0$  (using the equations in the beginning of this question). Similarly  $\varepsilon_2^2$  and  $\varepsilon_3^2$  are defined already.

Note that in terms of estimating  $(\mu, \theta_1)$  minimizing  $SSE$  is equivalent to maximizing  $\ln$  likelihood (conditional on  $\varepsilon_0$ ).

3. Find the unconditional variance of ARMA(1,1) model

$$y_t = \mu + \theta_1 \varepsilon_{t-1} + \varphi y_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim iid \text{WN}(0, \sigma^2)$$

Using stationarity and taking into account dependence between  $\varepsilon_{t-1}$  and  $y_{t-1}$

$$var(y_t) = \theta_1^2 \sigma^2 + \varphi^2 var(y_t) + 2\theta_1 \varphi cov(\varepsilon_t, y_t) + \sigma^2$$

$$\begin{aligned} cov(\varepsilon_t, y_t) &= \sigma^2 \text{ which can be found from } cov(\varepsilon_t, \mu + \theta_1 \varepsilon_{t-1} + \varphi y_{t-1} + \varepsilon_t) = \\ E(\varepsilon_t(\mu + \theta_1 \varepsilon_{t-1} + \varphi y_{t-1} + \varepsilon_t)) - E(\varepsilon_t)E(y_t) &= 0 + 0 + 0 + \sigma^2 - 0 = \sigma^2 \end{aligned}$$

The zeros are due to the fact that  $E(\varepsilon_t) = 0$ ,  $E(\varepsilon_t \varepsilon_{t-1}) = 0$  (white noise property),  $E(\varepsilon_t y_{t-1}) = 0$  (white noise property) and  $E(\varepsilon_t \varepsilon_t) = \sigma^2$ .

DETOUR: Note that white noise property does NOT imply that  $E(\varepsilon_t y_t) = 0$ . We can show that  $E(\varepsilon_{t-1} y_t) = (\theta_1 + \varphi)\sigma^2$  in this example.

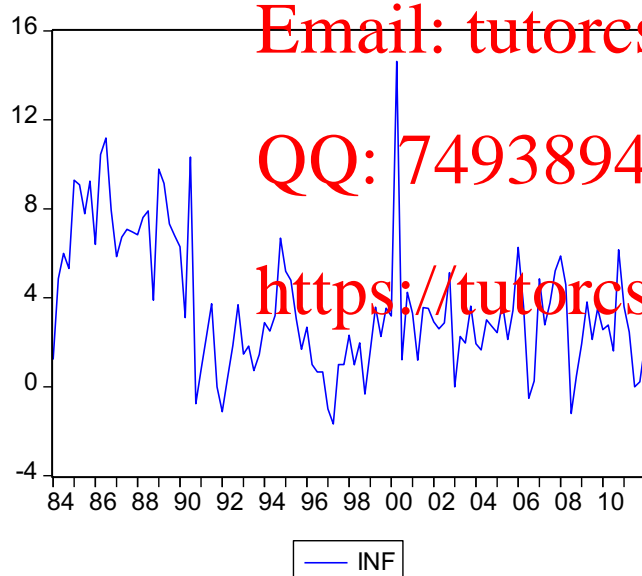
Hence,

$$\text{var}(y_t) = \frac{\sigma^2(1 + \theta_1^2 + \varphi^2 + 2\theta_1\varphi)}{1 - \varphi^2} = \sigma^2 \left( 1 + \frac{(\theta_1 + \varphi)^2}{1 - \varphi^2} \right)$$



#### 4. [Box-Jenkins methodology]

(a) The time series plot of INF shows that the inflation was on average lower after 1990 than before 1990. You may use the unit-root test with or without a time trend (by selecting or not selecting **Trend and intercept** in the unit root test pop-up menu). From the testing results below, the null of a unit root is rejected (very small p-values). Hence INF can be regarded as a stationary (or trend stationary) time series.



Augmented Dickey-Fuller Unit Root Test on INF		
Null Hypothesis: INF has a unit root		
Exogenous: Constant		
Lag Length: 1 (Automatic based on SIC, MAXLAG=12)		
	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-3.910993	0.0027
Test critical values: 1% level	-3.489117	
5% level	-2.887190	
10% level	-2.580525	

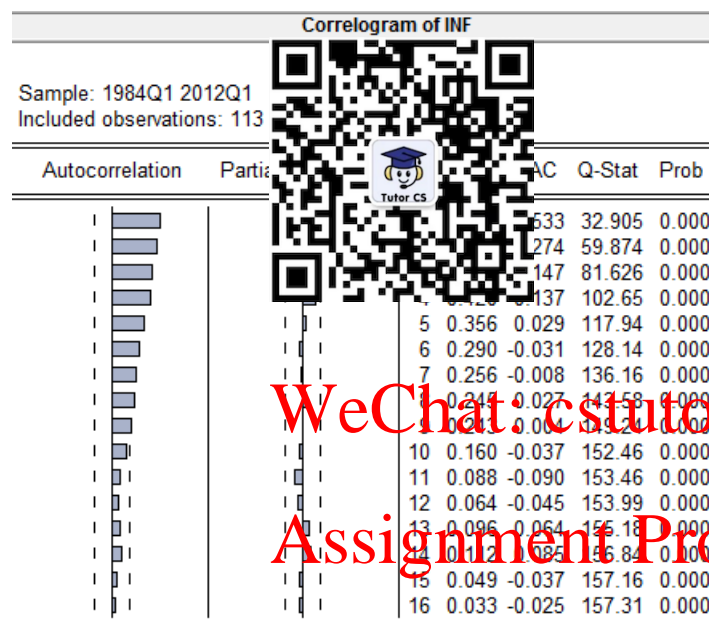
\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Unit Root Test on INF		
Null Hypothesis: INF has a unit root		
Exogenous: Constant, Linear Trend		
Lag Length: 1 (Automatic based on SIC, MAXLAG=12)		
	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-4.674579	0.0013
Test critical values: 1% level	-4.041280	
5% level	-3.450073	
10% level	-3.150336	

\*MacKinnon (1996) one-sided p-values.

(b) Visually, the correlogram of INF shows a PAC cutoff at lag  $j = 2$  with exponential decaying AC, which fits the cutoff pattern of an AR(2) model. On the other hand, the PAC

may also be interpreted as an exponential decay. For this reason, we consider the following models as candidates: AR(2), ARMA(1,1), ARMA(2,1), ARMA(1,2) and ARMA(2,2).

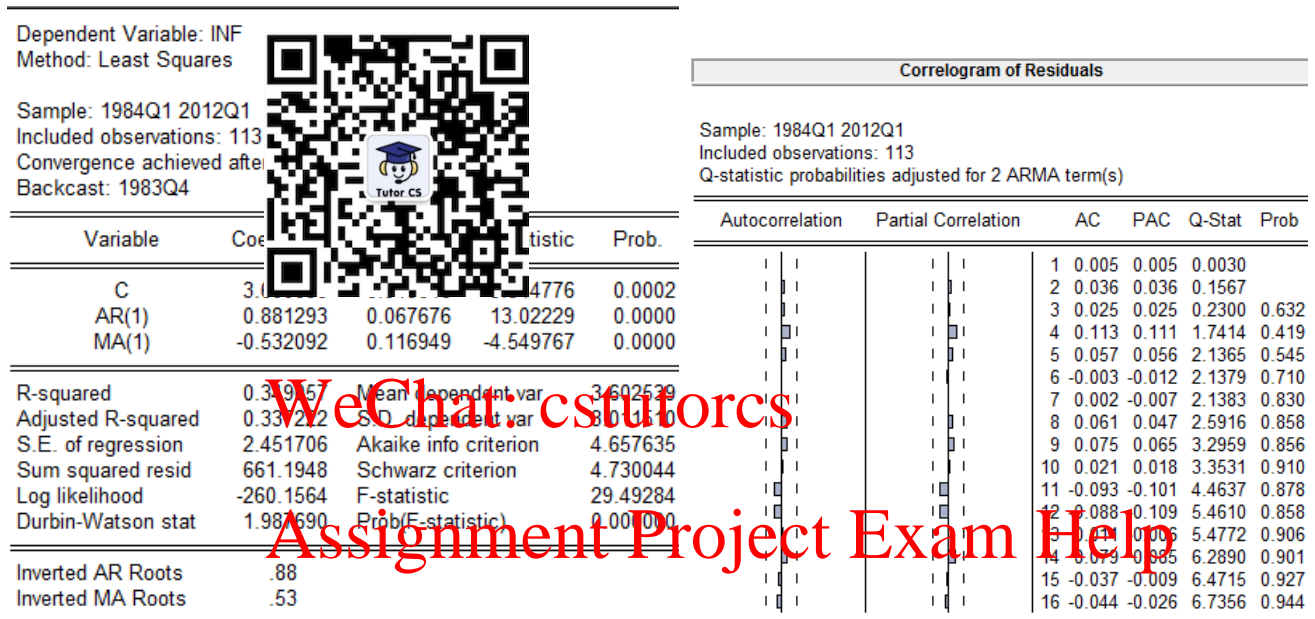


(c) The AIC and SIC values for the models considered in (b) are listed in the table below. Clearly, both AIC and SIC select ARMA(1,1).

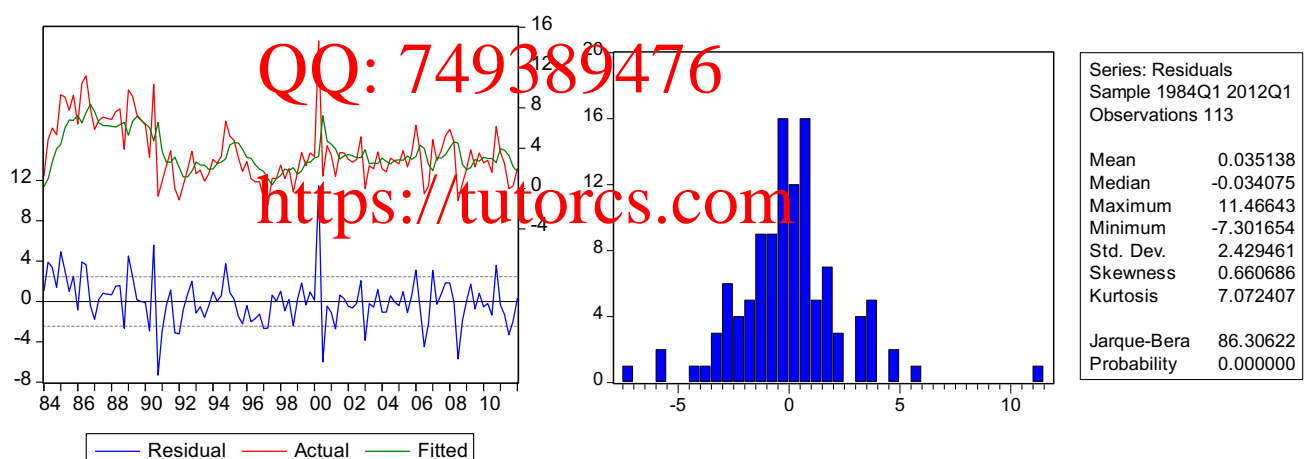
ARMA(p,q)	ARMA(2,0)	ARMA(1,1)	ARMA(2,1)	ARMA(1,2)	ARMA(2,2)
AIC	4.675253	4.657635	4.668168	4.673624	4.683174
SIC	4.747661	4.730044	4.764713	4.770169	4.803855

(d) The estimation output of ARMA(1,1) indicates that the roots of the AR polynomial and the MA polynomial are outside the unit circle (note that EViews reports inverted roots). There is no common root. The estimated ARMA coefficients are all statistically and economically significant. The residual-actual-fitted plot shows that the model fits the data quite well (also  $\bar{R}^2 = 0.337$ ), although a few residual points are beyond the 2-standard deviation bands. The key of an ARMA model is to capture the dependence structure in the time series. The residual from an adequate model should not exhibit autocorrelation. The residual correlogram of the ARMA(1,1) confirm that there are no autocorrelations in the residuals (large p-values, which are adjusted for the degrees of freedom lost in estimating the ARMA parameters). Further the histogram of the residual indicates that the normality is strongly rejected, which explains why a few residual points are outside the 2-se bands in the

residual plot. Overall, the ARMA(1,1) model is adequate in capturing the dependence structure in INF.

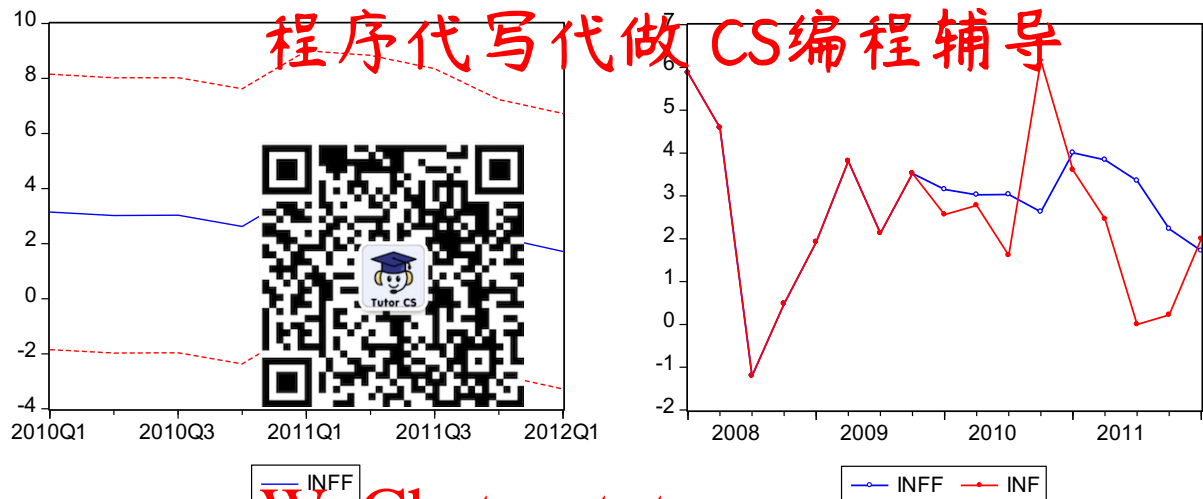


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(e) For the forecast exercise, you should be able to see the graphs below, where INFF (blue curve) stands for the 1-step ahead forecasts from the ARMA(1,1) model and INF (red curve) is the actual. The second graph is from the command “**plot inff inf**”. The first graph is from the **Forecast** menu, which includes the 2-se bands (dashed red lines). By comparison, the interval forecasts (2-se bands) in fact covered the actuals.





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