Midterm 1, Financial Econometrics, Econ 40357
University of Notre Dame
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Tuesday October 15, 2019

Choose the best answer.

1. Suppose $y_t = y_{t-1} + \epsilon_t,$ where $\epsilon_t \overset{iid}{\sim} \left(0, \sigma_\epsilon^2\right)$. The impulse response at time $t = 1, 2, 3, 4$ for a shock of size $\epsilon_1 = 1$ are,
   (a) $1, \quad 0.9, \quad (0.9)^2, \quad (0.9)^3$
   (b) $1, \quad 0.8, \quad 0, \quad 0$
   (c) $1, 1, 1, 1$
   (d) $1, 0, 0, 0$

2. Suppose $y_t = \rho y_{t-1} + \epsilon_t,$ where $\rho = 0.9$ and $\epsilon_t \overset{iid}{\sim} \left(0, \sigma_\epsilon^2\right)$. The impulse response at time $t = 1, 2, 3, 4$ for a shock of size $\epsilon_1 = 1$ are,
   (a) $1, \quad 0.9, \quad (0.9)^2, \quad (0.9)^3$
   (b) $1, \quad 0.8, \quad 0, \quad 0$
   (c) $1, 1, 1, 1$
   (d) $1, 0, 0, 0$

3. Suppose X_t has the normal distribution with mean $\mu = 100$ and variance $\sigma^2 = 20$.Then $\frac{E(X_t - \mu)^3}{\sigma^3} = \frac{E(X_t - 100)^3}{20^3}$ is
   (a) Negative
   (b) Positive
   (c) 0
   (d) 1

4. Suppose X_t has the student-t distribution with 4 degrees of freedom. It has mean $\mu = 100$ and variance $\sigma^2 = 20$.Then $\frac{E(X_t - \mu)^3}{\sigma^3} = \frac{E(X_t - 100)^3}{20^3}$ is
   (a) Negative
   (b) Positive
   (c) 0
   (d) 1

5. Suppose X_t has the student-t distribution with 4 degrees of freedom. It has mean $\mu = 100$ and variance $\sigma^2 = 20$.Then $\frac{E(X_t - \mu)4}{\sigma^4} = \frac{E(X_t - 100)^4}{20^4}$ is
   (a) Negative
   (b) Positive, but less than 3
   (c) Positive, but greater than 3
   (d) 1

6. Suppose Kai runs the Jarque-Bera test on a sample of data. Kai gets a value for the test statistic of 30 (the 5% critical value for a χ_2^2 is 5.99). He concludes

   (a) The observations are not independent
   (b) The observations are not stationary
   (c) The observations are not normally distributed
   (d) The observations are not persistent

7. Let x_t and y_t be stationary time series. When Louie runs the regression $y_t = \alpha + \beta x_t + \epsilon_t$, the slope is his estimator of

   (a) $\frac{Cov(y_t, x_t)}{Var(x_t)}$
   (b) $\frac{Cov(y_t, x_t)}{Var(y_t)}$
   (c) $\frac{Cov(y_t, x_t)}{\sqrt{Var(y_t)}} \sqrt{Var(x_t)}$
   (d) $E(y_t) - \beta E(x_t)$

8. Suppose $y_t = \rho y_{t-1} + \epsilon_t$, where $0 < \rho < 1$, and $\epsilon_t \overset{iid}{\sim} \left(0, \sigma_\epsilon^2\right)$. The optimal forecast of y_{t+3}, formed at time t is,

   (a) y_t
   (b) ρy_t
   (c) ρy_{t+2}
   (d) $\rho^3 y_t$

9. Suppose $y_t = \theta_1 \epsilon_t + \theta_2 \epsilon_{t-1} + \theta_3 \epsilon_{t-3}$, where $\epsilon_t \overset{iid}{\sim} \left(0, \sigma_\epsilon^2\right)$,and $\theta_1 + \theta_2 + \theta_3 = 1.2$.

   (a) y_t has a unit root
   (b) y_t is nonstationary
   (c) y_t is stationary
   (d) y_t is $i.i.d.$

10. Suppose $y_t = \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2}$, where $\epsilon_t \overset{iid}{\sim} \left(0, \sigma_\epsilon^2\right)$,and $\theta_1 + \theta_2 = 0.8$. The optimal forecast of y_{t+3} at time t is,

    (a) $\theta_1 \epsilon_{t+3} + \theta_2 \epsilon_{t+2} + \theta_3 \epsilon_{t+1}$
    (b) $\theta_1 \epsilon_t$
    (c) 0
    (d) y_t

11. Consider the regression $y_t = \alpha + \beta x_t + \epsilon_t$ where y_t and x_t are stationary time series. The $t-$ratio is $\tilde{\beta}/\text{se}\left(\hat{\beta}\right)$.That is, the least-squares estimate divided by its standard error. Typically, the Newey-West $t-$ratio will be smaller than the usual (standard) $t-$ratio because

    (a) The assumptions under which Newey-West is derived are more restrictive than that for the standard t-ratio
    (b) The assumptions under which Newey-West is derived are less restrictive than that for the standard t-ratio
    (c) The estimate of β under Newey-West is usually smaller than under standard least squares
    (d) None of the above

12. In maximum likelihood estimation, the parameters of the model are chosen such that

    (a) under the assumed model, we are most likely to have observed the actual data
    (b) under the alternative hypothesis, we would be most likely to have observed the actual data
    (c) the t-ratios are valid whether the observations are stationary or nonstationary
    (d) None of the above

13. In the AIC, $\ln\left(\hat{\sigma}_\epsilon^2\right) + \frac{2k}{T}$, $\ln\left(\hat{\sigma}_\epsilon^2\right)$ is,

    (a) apart from a factor of proportionality, the likelihood function
    (b) apart from a factor of proportionality, the negative of the likelihood function
    (c) apart from a factor of proportionality, the logarithm of the likelihood function
    (d) apart from a factor of proportionality, the negative of the logarithm of the likelihood function

14. In the AIC, $\ln\left(\hat{\sigma}_\epsilon^2\right) + \frac{2k}{T}$, the $\frac{2k}{T}$ part

    (a) is a penalty for adding parameters to the model
    (b) is a reward for adding parameters to the model
    (c) is the likelihood function
    (d) is the log likelihood function

15. Suppose $y_t = y_{t-1} + \epsilon_t$, and $x_t = x_{t-1} + \nu_t$, where $\epsilon_t \overset{iid}{\sim} \left(0, \sigma_\epsilon^2\right)$, and $\nu_t \overset{iid}{\sim} \left(0, \sigma_\nu^2\right)$. Sookie regresses y_t on x_t. As the sample size increases,

    (a) the slope coefficient converges to 0
    (b) the slope-coefficient diverges (it goes to infinity)
    (c) the $t-$ratio will indicate significance
    (d) the $t-$ratio will converge to 0

16. Suppose $y_t = y_{t-1} + \epsilon_t$, and $x_t = x_{t-1} + \nu_t$, where $\epsilon_t \overset{iid}{\sim} \left(0, \sigma_\epsilon^2\right)$, and $\nu_t \overset{iid}{\sim} \left(0, \sigma_\nu^2\right)$. We regress Δy_t on Δx_t. As the sample size increases,

    (a) the slope coefficient converges to 0
    (b) the slope-coefficient diverges (it goes to infinity)
    (c) the $t-$ratio will indicate significance
    (d) the $t-$ratio will converge to 0

17. Suppose Kai runs an Augmented Dickey-Fuller test on the regression $\Delta y_t = \alpha + \beta y_{t-1} + \delta_1 \Delta y_{t-1} + \delta_2 \Delta y_{t-2} + \delta_3 \Delta y_{t-3} + \epsilon_t$. He is testing

    (a) $\beta = \delta_1 = \delta_2 = \delta_3 = 1$
    (b) $\beta = 0$
    (c) $|\beta + \delta_1 + \delta_2 + \delta_3| < 1$
    (d) $|\delta_1 + \delta_2 + \delta_3| < 1$

18. Louie runs the predictive regression $\sum_{j=1}^{10} r^e_{t+j} = \alpha + \beta \left(\frac{d_t}{p_t}\right) + \epsilon_{t+10}$ where r^e_t is the one-year excess return on the market, and d_t/p_t is the dividend yield on the market. Louie finds $\hat{\beta} > 0$ and statistically significant with Newey-West t-ratio. Louie can conclude, this is evidence of

    (a) a pro-cyclical risk premium
    (b) a counter-cyclical risk premium
    (c) the Newey-West t-ratio is biased upwards
    (d) the beta-risk model doesn't work

19. If excess returns are given by the single-factor representation, $r^e_{t,i} = \alpha_i + \beta_i f_t + \epsilon_{t,i}$ for each asset $i = 1, ..., n$, where $r^e_{t,i}$ is the excess return on asset i and f_t is factor, then

    (a) β_i is asset $i's$ exposure to the (risk) factor
    (b) The mean excess returns of these assets vary proportionally to their betas
    (c) $\alpha_1 = \alpha_2 = \cdots \alpha_n = 0$
    (d) all of the above

20. (pure extra credit) In Louie's regression from question 18, the regression error

    (a) follows an MA(10)
    (b) follows an MA(9)
    (c) is independent and identically distributed
    (d) is serially uncorrelated