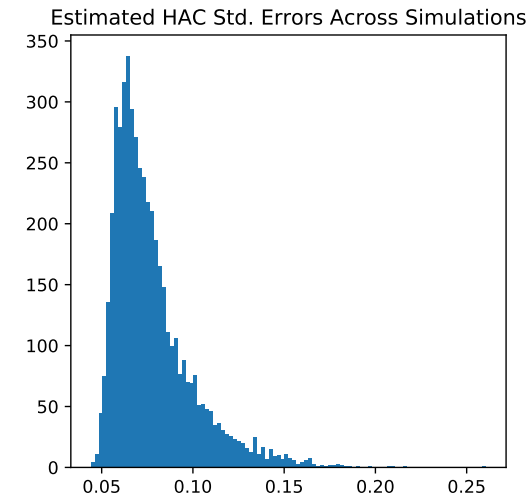
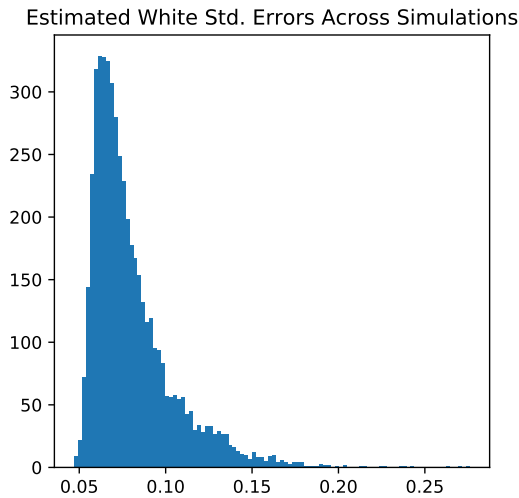
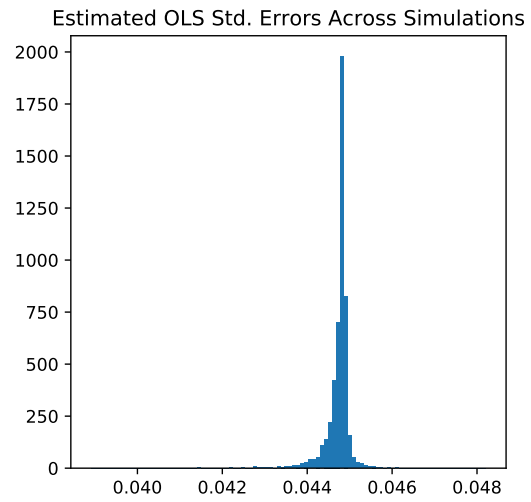
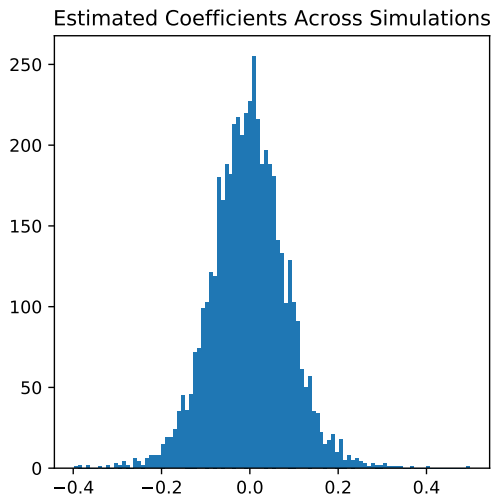


Problem Set 2  
ECON 6413–Ng  
Miguel Acosta  
September 22, 2017

**Q1.** In the results below, I've assumed that  $v_t \sim N(0, 1)$ , as in Hamilton (2008). I am able to replicate table 2 of Hamilton (2008). Here are the results for  $T = 500$  and 5000 replications:

| Standard Error | Size  |
|----------------|-------|
| OLS            | 0.280 |
| White          | 0.062 |
| HAC, $q = 5$   | 0.062 |

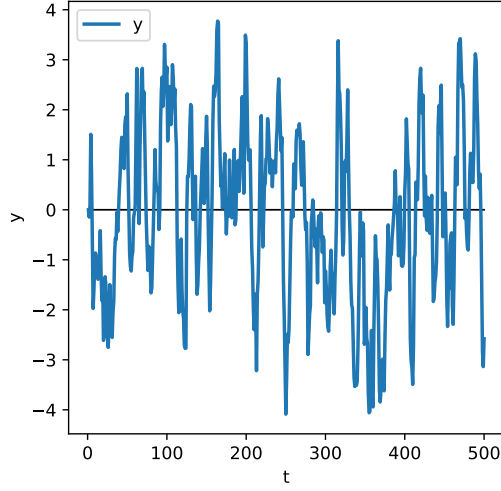
For fun, here are the distributions of the  $\hat{\beta}$  and standard errors across the simulations.



**Q2.** We are considering an ARMA(1,1):

$$y_t = \alpha y_{t-1} + \beta e_{t-1} + e_t \quad e_t \sim N(0, \sigma^2)$$

Here is a simulated series with 500 time periods and  $\beta \equiv (\alpha, \beta, \sigma^2) = (0.8, 0.5, 0.5)$ .



i. In problem set 1, I calculated  $\gamma_0$  and  $\gamma_1$  as:

$$\gamma_0 = \frac{\sigma^2(2\alpha\beta + \beta^2 + 1)}{1 - \alpha^2} \quad \gamma_1 = \sigma^2 \cdot \frac{\alpha^2\beta + \beta^2\alpha + \beta + \alpha}{1 - \alpha^2}. \quad (1)$$

Remember that the series is mean-0. So, the second-order autocovariance is:

$$\gamma_2 = \mathbb{E}[y_t y_{t-2}] = \alpha y_{t-1} y_{t-2} + \beta e_{t-1} y_{t-2} + e_t y_{t-2} = \alpha \gamma_1 \quad (2)$$

ii. The GMM objective function, therefore, is:

$$\bar{g}(\theta) \equiv \frac{1}{T-3} \sum_{t=3}^T \hat{\psi} - \gamma(\theta) = \frac{1}{T-3} \sum_{t=3}^T \begin{bmatrix} y_t^2 - \frac{\sigma^2(2\alpha\beta + \beta^2 + 1)}{1 - \alpha^2} \\ y_t y_{t-1} - \sigma^2 \cdot \frac{\alpha^2\beta + \beta^2\alpha + \beta + \alpha}{1 - \alpha^2} \\ y_t y_{t-2} - \alpha \sigma^2 \cdot \frac{\alpha^2\beta + \beta^2\alpha + \beta + \alpha}{1 - \alpha^2} \end{bmatrix}$$

Results follow:

|            |        |
|------------|--------|
| $\alpha$   | 0.8315 |
| $\beta$    | 0.4478 |
| $\sigma^2$ | 0.4546 |

- iii. The third and fourth centered moments of an ARMA(1, 1) will be difficult to calculate, as you can see here (thanks to SymPy for these expressions):

$$\begin{aligned}\mathbb{E}[y_t^3] &= \mathbb{E}[\alpha^3 y_{t-1}^3 + 3\alpha^2 \beta e_{t-1} y_{t-1}^2 + 3\alpha^2 e_t y_{t-1}^2 + 3\alpha \beta^2 e_{t-1}^2 y_{t-1} \\ &\quad + 6\alpha \beta e_{t-1} e_t y_{t-1} + 3\alpha e_t^2 y_{t-1} + \beta^3 e_{t-1}^3 + 3\beta^2 e_{t-1}^2 e_t + 3\beta e_{t-1} e_t^2 + e_t^3] \\ \mathbb{E}[y_t^4] &= \mathbb{E}[\alpha^4 y_{t-1}^4 + 4\alpha^3 \beta e_{t-1} y_{t-1}^3 + 4\alpha^3 e_t y_{t-1}^3 + 6\alpha^2 \beta^2 e_{t-1}^2 y_{t-1}^2 \\ &\quad + 12\alpha^2 \beta e_{t-1} e_t y_{t-1}^2 + 6\alpha^2 e_t^2 y_{t-1}^2 + 4\alpha \beta^3 e_{t-1}^3 y_{t-1} + 12\alpha \beta^2 e_{t-1}^2 e_t y_{t-1} \\ &\quad + 12\alpha \beta e_{t-1} e_t^2 y_{t-1} + 4\alpha e_t^3 y_{t-1} + \beta^4 e_{t-1}^4 + 4\beta^3 e_{t-1}^3 e_t + 6\beta^2 e_{t-1}^2 e_t^2 \\ &\quad + 4\beta e_{t-1} e_t^3 + e_t^4]\end{aligned}$$

Luckily, most of these terms are 0, or simplify substantially. In particular, note that

$$\mathbb{E}[f(e_t)y_{t-1}] = \mathbb{E}[e_t e_{t-1} y_{t-1}] = \mathbb{E}[e_t f(y_{t-1})] = 0 \quad \mathbb{E}[e_t^3] = 0 \quad \mathbb{E}[e_t^4] = 3\sigma^4$$

The first expression is therefore:

$$\mathbb{E}[y_t^3] = \alpha^3 \mathbb{E}[y_{t-1}^3] \implies \mathbb{E}[y_{t-1}^3] =$$

(assuming  $\mathbb{E}[y_0^3] = 0$ , which is consistent with the assumption that  $y_0 = 0$ ). The second expression reduces to

$$\mathbb{E}[y_t^4] = \alpha^4 \mathbb{E}[y_{t-1}^4] + 3\sigma^4(\beta^4 + 4\alpha\beta^3 + 6\alpha^2\beta^2 + 4\alpha^3\beta + 1).$$

Since we only have covariance stationarity, the 4th moment depends on time, and can be calculated recursively assuming  $\mathbb{E}[y_t^4] = 0$ .

With all this, I present results that didn't work.

|            |         |
|------------|---------|
| $\alpha$   | -0.8128 |
| $\beta$    | 0.9982  |
| $\sigma^2$ | 2.5513  |

- Q3. i. Remember what OLS does:

$$\begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} = \begin{bmatrix} \gamma_0 & \gamma_1 \\ \gamma_1 & \gamma_0 \end{bmatrix}^{-1} \begin{bmatrix} \gamma_1 \\ \gamma_2 \end{bmatrix}$$

We can take advantage of the expressions in 1 and 2 to back out the estimates for  $(\alpha, \beta, \sigma^2)$ . Multiply both sides by the projection matrix to get

$$\begin{bmatrix} \gamma_0 & \gamma_1 \\ \gamma_1 & \gamma_0 \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} = \begin{bmatrix} \gamma_1 \\ \gamma_2 \end{bmatrix}$$

We can estimate the RHS easily. So, this identifies  $\alpha$  since  $\frac{\gamma_2}{\gamma_1} = \alpha$ . Next, taking the ratio of  $\gamma_0$  to  $\gamma_1$ , we have one equation to solve for  $\hat{\beta}$ . I asked SymPy to do this. Finally, we can use the  $\gamma_0$  equation to get  $\sigma^2$ .

- ii. The OLS estimates are:

|          | Estimate | Newey-West S.E. |
|----------|----------|-----------------|
| $\phi_1$ | 1.2144   | 0.0394          |
| $\phi_2$ | -0.3424  | 0.0393          |

The estimate of  $\phi(1)$  is 0.87 [0.017]. The number in brackets is the Newey-West standard error with  $q = 5$ . Inverting this to get the parameters of the ARMA(1, 1) model as discussed in the previous subquestion results in:

|            |        |
|------------|--------|
| $\alpha$   | 0.8315 |
| $\beta$    | 0.4168 |
| $\sigma^2$ | 0.4717 |

- iii. I don't know what this means...

**Q4.** I went with question (i). Here are the results for SMM, using autocovariances of order 0, 1, and 2 as the moment conditions:

|            |        |
|------------|--------|
| $\alpha$   | 0.8383 |
| $\beta$    | 0.4365 |
| $\sigma^2$ | 0.4573 |

Here are the results using indirect inference, with an AR(2) as the auxiliary model:

|            |        |
|------------|--------|
| $\alpha$   | 0.8405 |
| $\beta$    | 0.4379 |
| $\sigma^2$ | 0.5000 |

For each of the results above, I used 501 simulations, and kept  $T = 500$ . I used the same sample of iid shocks in both simulation estimations.