Answers to final exam

1.) a.) plim(b) = $\Sigma_{xx}^{-1}\Sigma_{xy}$

b.) (1) if for the β we are interested in it is the case that $E(y_t - \mathbf{x}'_t \beta)\mathbf{x}_t = \mathbf{0}$, then OLS is allowing us to estimate this β . (2) If our goal is to minimize the mean squared error of a forecast of y_t using a linear function of \mathbf{x}_t , $\hat{y}_t = \mathbf{x}'_t \beta$, then the plim of the regression is the optimal β to use.

2a.) Let $\hat{\boldsymbol{\alpha}} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y}, s^2 = (T-3)^{-1}\Sigma(y_t - \mathbf{x}'_t\hat{\boldsymbol{\alpha}})^2$, and $\mathbf{1}' = (1,1,1)$. Then reject H_0 if

$$\frac{\mathbf{1}'\hat{\boldsymbol{\alpha}} - 1}{\sqrt{s^2\mathbf{1}'(\mathbf{X}'\mathbf{X})^{-1}\mathbf{1}}} < z$$

where z is the number such that the probability that a Student t variable with T-3 degrees of freedom is less than z is equal to 0.05, so z is about -1.66. This is an exact small-sample test under the assumptions.

b.) Let $\mathbf{S} = \Sigma \hat{u}_t^2 \mathbf{x}_t \mathbf{x}_t'$ and reject H_0 if

$$\frac{(\mathbf{1}'\hat{\boldsymbol{\alpha}}-1)^2}{s^2\mathbf{1}'(\mathbf{X}'\mathbf{X})^{-1}\mathbf{S}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{1}} > z$$

where z = 3.84, the number such that the probability that at $\chi^2(1)$ variable exceeds z is 0.05. This test is only a large-sample approximation under the stated conditions.

c.) A constant term should have been included in the regression- could have tested with simple t test. One would also suspect serial correlation or even spurious regression. Could test for this by regressing \hat{u}_t on \mathbf{x}_t and \hat{u}_{t-1} and calculating a t-test that the coefficient on \hat{u}_{t-1} is zero. Would also worry about endogeneity, e.g., when productivity is unusually high $(\varepsilon_t > 0)$, the firm probably wants to hire more labor (ℓ_t positively correlated with ε_t). To test for this we'd need an instrument (something correlated with ℓ_t but uncorrelated with ε_t).

3.) a.) no
b.)
$$\mathbf{g}(\boldsymbol{\theta}, \mathbf{Y}_{T}) = T^{-1} \Sigma \mathbf{x}_{t}(y_{t} - \mathbf{z}_{t}^{'} \boldsymbol{\theta}), \mathbf{S} = \sigma^{2} \Sigma_{xx}, \mathbf{D}^{'} = -\Sigma_{xz}$$

c.) $\mathbf{\hat{S}} = \hat{\sigma}^{2} T^{-1} \Sigma \mathbf{x}_{t} \mathbf{x}_{t}^{'}, \ \hat{\sigma}^{2} = T^{-1} \Sigma (y_{t} - \mathbf{z}_{t}^{'} \boldsymbol{\hat{\theta}})^{2}, \ \mathbf{\hat{D}} = -T^{-1} \Sigma \mathbf{z}_{t} \mathbf{x}_{t}^{'}$
d.) GMM FOC gives

$$\left(-T^{-1}\Sigma\mathbf{x}_{t}\mathbf{z}_{t}^{'}\right)^{'}\hat{\sigma}^{-2}\left(T^{-1}\Sigma\mathbf{x}_{t}\mathbf{x}_{t}^{'}\right)^{-1}\left(T^{-1}\Sigma\mathbf{x}_{t}(y_{t}-\mathbf{z}_{t}^{'}\hat{\boldsymbol{\theta}}\right)=\mathbf{0}$$

which on rearranging is 2SLS.

e.)

$$J = T \left(T^{-1} \Sigma \mathbf{x}_t \hat{u}_t \right)' \left(\hat{\sigma}^{-2} T^{-1} \Sigma \mathbf{x}_t \mathbf{x}_t' \right)^{-1} \left(T^{-1} \Sigma \mathbf{x}_t \hat{u}_t \right)$$
$$= \frac{\left(\Sigma \hat{u}_t \mathbf{x}_t' \right) \left(\Sigma \mathbf{x}_t \mathbf{x}_t' \right)^{-1} \left(\Sigma \mathbf{x}_t \hat{u}_t \right)}{\hat{\sigma}^2} \approx \chi^2 (r - a)$$

f.) Use

$$\frac{\left(\Sigma u_t \mathbf{x}_t'\right) \left(\Sigma \mathbf{x}_t \mathbf{x}_t'\right)^{-1} \left(\Sigma \mathbf{x}_t u_t\right)}{\hat{\sigma}^2}$$

for $u_t = y_t - \mathbf{z}_t' \boldsymbol{\theta}_0$. We have here conditions for m.d.s. CLT,

$$T^{-1/2} \Sigma \mathbf{x}_t u_t \xrightarrow{L} N(\mathbf{0}, \sigma^2 \Sigma_{xx})$$

and so

$$\frac{\left(T^{-1/2}\Sigma u_t \mathbf{x}_t'\right) \left(T^{-1}\Sigma \mathbf{x}_t \mathbf{x}_t'\right)^{-1} \left(T^{-1/2}\Sigma \mathbf{x}_t u_t\right)}{\hat{\sigma}^2}$$

$$\xrightarrow{L} T^{-1/2}\Sigma u_t \mathbf{x}_t' (\sigma^2 \mathbf{\Sigma}_{xx})^{-1} \left(T^{-1/2}\Sigma \mathbf{x}_t u_t\right)$$

$$\xrightarrow{L} \chi^2(r)$$