Midterm Exam Sample Answers
Spring 2007

1. Solving the square:

$$\frac{1}{n}\sum_{i=1}^{n}\left(w\hat{e}_i+(1-w)\,\tilde{e}_i\right)^2 = w^2\frac{1}{n}\sum_{i=1}^{n}\hat{e}_i^2+2w\,(1-w)\,\frac{1}{n}\sum_{i=1}^{n}\hat{e}_i\tilde{e}_i+(1-w)^2\,\frac{1}{n}\sum_{i=1}^{n}\tilde{e}_i^2$$

Now using matrix notation

$$\frac{1}{n}\sum_{i=1}^{n}\hat{e}_i\tilde{e}_i=\hat{e}'\tilde{e}=\frac{1}{n}y'MM_1y=\frac{1}{n}y'My=\frac{1}{n}\hat{e}'\hat{e}=\hat{\sigma}^2$$

where $M=I-X\left(X'X\right)^{-1}X'$, $M_1=I-X_1\left(X_1'X_1\right)^{-1}X_1'$ and $X=[X_1,X_2]$. The third inequality uses the fact that since X_1 lies in the span of X, $MM_1=M$.

$$y'\left(I-P-P_1+P_1\right)y=y'\left(I-P\right)y=.$$

This means that the top equation simplies to

$$\left(w^2+2w\,(1-w)\right)\hat{\sigma}^2+(1-w)^2\,\tilde{\sigma}^2=(1-a)\,\hat{\sigma}^2+a\tilde{\sigma}^2$$

if we set

$$a=(1-w)^2\,,$$

noting that

$$1-(1-w)^2=w^2+2w\,(1-w)\,.$$

2.

$$\begin{aligned}
\frac{1}{n}\operatorname{tr}(MD) &= \frac{1}{n}\operatorname{tr}\left(\left(I-X\left(X'X\right)^{-1}X'\right)D\right)\\
&= \frac{1}{n}\operatorname{tr}(D)-\operatorname{tr}\left(X\left(X'X\right)^{-1}X'D\right)\\
&= \frac{1}{n}\sum_{i=1}^{n}\sigma_i^2-\frac{1}{n}\operatorname{tr}\left(\left(\frac{1}{n}X'X\right)^{-1}\left(\frac{1}{n}X'DX\right)\right)\\
&= \frac{1}{n}\sum_{i=1}^{n}\sigma_i^2-\frac{1}{n}b_n
\end{aligned}$$

where

$$b_n=\operatorname{tr}\left(\left(\frac{1}{n}X'X\right)^{-1}\left(\frac{1}{n}X'DX\right)\right).$$

Now

$$
\begin{aligned}
\frac{1}{n}X'X &= \frac{1}{n}\sum_{i=1}^{n} x_i x_i' \xrightarrow{p} E\left(x_i x_i'\right) = Q \\
\frac{1}{n}X'DX &= \frac{1}{n}\sum_{i=1}^{n} x_i x_i' \sigma_i^2 \xrightarrow{p} E\left(x_i x_i' \sigma_i^2\right)
\end{aligned}
$$

and

$$
\begin{aligned}
E\left(x_i x_i' \sigma_i^2\right) &= E\left(x_i x_i' E\left(e_i^2 \mid x_i\right)\right) \\
&= E\left(E\left(x_i x_i' e_i^2 \mid x_i\right)\right) \\
&= E\left(x_i x_i' e_i^2\right) \\
&= \Omega.
\end{aligned}
$$

Thus $b_n \xrightarrow{p} \operatorname{tr}\left(Q^{-1}\Omega\right).$

Cautionary Remark: Common mistakes include mis-using the matrix manipulations, substituting between σ_i^2, e_i^2 and $\hat{e}_i^2$ in definitions.

3. A good test for H_0 is the Wald test. This is appropriate in this context because the estimator is least-squares and the hypothesis is a linear restriction on the least-squares coefficients. Let $k = \dim(\beta_1) = \dim(\beta_2)$. (Note that β_1 and β_2 must have the same number of elements otherwise the hypothesis does not make sense. Furthermore, while the dimensions of β_1 and β_2 are not given, the use of the transpose operator clearly suggests that they are vectors, not scalars. Thus it is inappropriate to simply assume that $k = 1$, which was a common error.)

   The hypothesis can be written in the linear form

$$
H_0 : R'\beta = 0
$$

   where

$$
R = \begin{pmatrix} I_k \\ -I_k \end{pmatrix}.
$$

   First, estimate the model by least-squares. The coefficient estimate is

$$
\hat{\beta} = \left(X'X\right)^{-1}\left(X'y\right).
$$

   An estimate of the asymptotic covariance matrix is

$$
\begin{aligned}
\hat{V} &= \hat{Q}^{-1}\hat{\Omega}\hat{Q}^{-1} \\
\hat{Q} &= \frac{1}{n}X'X \\
\hat{\Omega} &= \frac{1}{n}\sum_{i=1}^{n} x_i x_i' \hat{e}_i^2 \\
\hat{e}_i &= y_i - x_i'\hat{\beta}
\end{aligned}
$$

The Wald statistic for H_0 against H_1 is

$$W_n = n\hat{\beta}' R \left(R'\hat{V}R \right)^{-1} R'\hat{\beta}$$

You can also write it as

$$W_n = n \left(\hat{\beta}_1 - \hat{\beta}_2 \right)' \left(\hat{V}_{11} - \hat{V}_{21} - \hat{V}_{12} + V_{22} \right)^{-1} \left(\hat{\beta}_1 - \hat{\beta}_2 \right).$$

I would select the 5% level, and would use an asymptotic test. The asymptotic test would reject H_0 in favor of H_1 if W_n exceeds the 5% critical value of the χ^2_k distribution. The χ^2_k distribution is used since W_n is asymptotically χ^2_k under H_0.

Alternatively, I could use a bootstrap test.

Since the model does not assume that the error is homoskedastic, it would be inappropriate to use an F statistic, or a Wald statistic constructed using the homoskedastic covariance matrix estimator.

4. Studying a list of t-ratios to find "the key predictor" can be quite misleading. One way to understand this deficiency is that the researcher is effectively looking for the largest t-ratio in a set of 20. While any individual t-ratio might be approximately normally distributed, the maximum over a set of 20 t-ratios is not normally distributed. It should not be surprising to see one "significant" t-ratio among a set of 20, even if all the coefficients are truly zero.

   To make a formal argument, suppose all of the coefficients are zero and the covariance matrix V is diagonal, so the t-ratios $T_j \to_d Z_j \sim N(0,1)$ and are mutually independent. We can then calculate the probability that one of the 20 t-ratios is "significant" in the sense of exceeding 2 in absolute value. We calculate that

$$P\left(\max_{1\le j\le 20} |T_j| \le 2 \right) \to P\left(\max_{1\le j\le 20} |Z_j| \le 2 \right) = P\left(|Z_j| \le 2 \right)^{20} = (0.95)^{20} = 0.36.$$

   Therefore, under the hypothesis that all coefficients are zero, the probability that the largest t-ratio exceeds 2 is approximately 64%. It is hardly surprising that this occurs.

   The researcher actually observed 2.5, which is somewhat less likely. Indeed

$$P\left(\max_{1\le j\le 20} |T_j| \le 2.5 \right) \to (0.99)^{20} = 0.82.$$

   Thus the probability of observing a t-ratio this large (under the hypothesis that all coefficients are truly zero) is approximately 18%. While somewhat unlikely, this is still insignificant by conventional standards.