

Queen's University
School of Graduate Studies and Research
Department of Economics

Economics 850

Fall, 2024

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Answers to Midterm Examination

October 24, 2024.

Time Limit: 80 minutes

Please answer all 3 questions. The marks for each question are shown in square brackets. All answers should be as short as it is reasonably possible to make them.

1. You are given an N -vector \mathbf{y} and an $N \times k$ matrix \mathbf{X} , with $N > k$. You regress \mathbf{y} on \mathbf{X} to obtain $\hat{\boldsymbol{\beta}}$, a residual vector $\hat{\mathbf{u}}$, and a vector of fitted values $\hat{\mathbf{y}}$.

- a) Suppose you regress \mathbf{y} on $\hat{\mathbf{y}}$. What can you say about the coefficient estimate? How will the SSR from this regression compare with the one from the original regression?
- b) Suppose you regress $\hat{\mathbf{u}}$ on \mathbf{X} . What can you say about the coefficient estimates? How will the SSR from this regression compare with the one from the original regression?
- c) Suppose you create a dummy variable \mathbf{d} equal to 1 for observation 1 and equal to 0 for all other observations. If you regress \mathbf{y} on \mathbf{X} and \mathbf{d} , how will the SSR from this regression compare with the one from the original regression? How will it compare with the original sum of squared residuals for observations 2 through N only?
- d) For the regression of part c), how is the coefficient on \mathbf{d} related to the first element of $\hat{\mathbf{u}}$? Could you have calculated this coefficient without running this regression?

[32 marks]

NOTE: Parts of answers in square brackets are just explanations, in case students don't understand. The correct answers are not expected to include them.

ANSWER [8 marks for each part]

- a) The estimated coefficient will be 1. The SSR will be identical to the one from the original regression. [The coefficient must be 1, because $\hat{\mathbf{y}} = \mathbf{X}\hat{\boldsymbol{\beta}}$ minimizes the SSR. For any other value, the SSR would be larger. This also shows that the SSR must be identical to the one from the original regression.]
- b) The coefficient estimates will all be 0. The SSR will be identical to the one from the original regression. [We know the coefficients are all 0, because $\hat{\mathbf{u}}$ is

orthogonal to \mathbf{X} . Since $\hat{\mathbf{u}}$ is just the vector of residuals, its sum of squares is unchanged by regressing it on \mathbf{X} .]

- c) The SSR will be smaller than the original one, because observation 1 will now fit perfectly. It will also be smaller than the original SSR for observations 2 through N only, [because the estimate of β will now minimize the SSR for those observations.]
- d) The coefficient on \mathbf{d} must be larger in absolute value than the first element of $\hat{\mathbf{u}}$, because it is equal to $\hat{u}_1/(1-h_1)$, and $0 < h_1 < 1$. This also answers the second part of the question. We just compute the coefficient on \mathbf{d} as $\hat{u}_1/(1-h_1)$.

2. Consider the model

$$y_i = \beta_1 + \beta_2 d_i + u_i, \quad u_i \sim \text{IID}(0, \sigma^2), \quad i = 1, \dots, N, \quad (1)$$

where d_i is a binary variable that equals either 0 or 1.

- a) Under the stated assumptions, explain how to construct a 95% confidence interval for β_2 . Is this interval exact in finite samples? Why or why not?
- b) Consider two different samples for the model (1). One has $\sigma = 1$ and $N = 50$, and the other has $\sigma = 2$ and $N = 200$. Under what circumstances, if any, would you expect the 95% confidence intervals for β_2 from the two samples to be roughly the same length? Explain.
- c) Suppose the probability that $d_i = 1$ is δ and may vary across samples. If you have two independent samples with $N = 100$ and the same value of σ , but one has $\delta = 0.2$ and one has $\delta = 0.25$, which sample will probably yield the shortest confidence interval. Will this be true for every such pair of samples? Explain.

[30 marks]

ANSWER [10 marks for each part]

- a) This is the usual confidence interval based on the $t(N-2)$ distribution and the OLS standard error for $\hat{\beta}_2$. [Students do not need to write it down explicitly.] The interval is not exact in finite samples, because the u_i are not assumed to be normally distributed.
- b) They will be roughly (but not exactly) the same length if the proportion of 1s in \mathbf{d} were the same in the two samples.

[Quadrupling the sample size should halve the standard error on $\hat{\beta}_2$, but doubling σ should double it. Thus, if the matrix $\mathbf{X}^\top \mathbf{X}/N$ were unchanged and s/σ were unchanged, the confidence interval would be unchanged. The matrix will be unchanged if the proportion of 1s in \mathbf{d} were the same, but s will almost certainly be different, so the CIs still won't be exactly the same length.]

[Of course, for any actual samples, the two $\mathbf{X}^\top \mathbf{X}/N$ matrices will probably differ, and the two values of s will almost certainly also differ. Thus either interval could be longer, and with such small samples the differences could be substantial.]

- c) The actual proportion of 1s in \mathbf{d} matters greatly. The closer it is to 0.5, the more efficiently β_2 will be estimated. Thus we would expect the CI to be shorter, most of the time, for $\delta = 0.25$ than for $\delta = 0.2$. But this will not be true all the time, because the actual proportion of 1s may differ substantially from δ . The sample variance of the disturbances also matters. The larger it is, the longer will be the CI.

[It is the actual proportion of 1s in the sample that matters, not the expected proportion. Given the small sample size, there are bound to be some samples with $\delta = 0.20$ that have more 1s than the other sample with $\delta = 0.25$. Similarly, it is the actual value of s that matters, not σ .]

3. Consider the linear regression model

$$\mathbf{y} = \mathbf{X}_1\beta_1 + \mathbf{X}_2\beta_2 + \mathbf{u}, \quad \mathbf{u} \sim \text{NID}(\mathbf{0}, \sigma^2\mathbf{I}), \quad (2)$$

where there are N observations and $k = k_1 + k_2$ regressors, with the regressors in \mathbf{X}_1 exogenous and the ones in \mathbf{X}_2 predetermined but not exogenous.

- Write the F statistic for $\beta_2 = \mathbf{0}$ explicitly as a function of N , k , k_2 , \mathbf{y} , \mathbf{X}_1 , and \mathbf{X}_2 . It will probably be convenient to use projection matrices that project onto or off the subspaces spanned by \mathbf{X}_1 , \mathbf{X}_2 , and/or $\mathbf{X} = [\mathbf{X}_1 \ \mathbf{X}_2]$.
- To what distribution should you compare the F statistic of part a)? Will this F statistic be exactly distributed according to this distribution? Will it follow this distribution asymptotically? Explain briefly.
- Write down the Wald statistic for $\beta_2 = \mathbf{0}$ in the model (2). How is it related to the F statistic of part a)? How is it distributed asymptotically under the null hypothesis?
- When the null hypothesis is true, the Wald statistic of part c) must be $O_p(N^a)$. When $\beta_2 = \beta_2^0 \neq \mathbf{0}$, the Wald statistic must instead be $O_p(N^b)$. Exactly what are the values of a and b here?

[38 marks]

ANSWER [10, 8, 10, 10]

- a) The FWL regression is

$$\mathbf{M}_1\mathbf{y} = \mathbf{M}_1\mathbf{X}_2\beta_2 + \text{resids.}$$

The numerator of the F statistic is the ESS from this regression, divided by k_2 . The denominator is the SSR for either the original regression or the FWL regression, divided by k . Thus

$$F = \frac{\mathbf{y}^\top \mathbf{M}_1 \mathbf{X}_2 (\mathbf{X}_2^\top \mathbf{M}_1 \mathbf{X}_2)^{-1} \mathbf{X}_2^\top \mathbf{M}_1 \mathbf{y} / k_2}{\mathbf{y}^\top \mathbf{M}_X \mathbf{y} / (n - k)}.$$

- b) Compare the F statistic to the $F(k_2, N - k)$ distribution. The test is not exact, because \mathbf{X}_2 is not exogenous. But it will be asymptotically valid, because the denominator tends to 1 and k_2 times the numerator tends to $\chi^2(k_2)$.
- c) The Wald statistic uses the facts that

$$\hat{\beta}_2 = (\mathbf{X}_2^\top \mathbf{M}_1 \mathbf{X}_2)^{-1} \mathbf{X}_2^\top \mathbf{M}_1 \mathbf{y}$$

and

$$\widehat{\text{Var}}(\hat{\beta}_2) = s^2 (\mathbf{X}_2^\top \mathbf{M}_1 \mathbf{X}_2)^{-1}.$$

Thus, because $\mathbf{X}_2^\top \mathbf{M}_1 \mathbf{X}_2^{-1} (\mathbf{X}_2^\top \mathbf{M}_1 \mathbf{X}_2)^{-1} = \mathbf{I}$, the Wald statistic is

$$\frac{1}{s^2} \mathbf{y}^\top \mathbf{M}_1 \mathbf{X}_2 (\mathbf{X}_2^\top \mathbf{M}_1 \mathbf{X}_2)^{-1} \mathbf{X}_2^\top \mathbf{M}_1 \mathbf{y}.$$

This is equal to k_2 times the F statistic. It is asymptotically distributed as $\chi^2(k_2)$.

[It is *not* acceptable just to write down the general formula for a Wald test of the restrictions that $\beta = \mathbf{0}$ or the general linear restrictions $\mathbf{R}\beta = \mathbf{r}$, because doing this does not show the relationship to the F statistic.]

- d) Clearly, $a = 0$ and $b = 1$. [Under the null hypothesis, any asymptotically valid test statistic must be $O_p(1)$; hence $a = 0$. Under the alternative, the noncentrality parameter

$$\frac{1}{\sigma^2} \beta_2^\top \mathbf{X}_2^\top \mathbf{M}_1 \mathbf{X}_2 \beta_2$$

is evidently $O_p(n)$. This is the leading-order term, and so the test statistic itself must also be $O_p(n)$; hence $b = 1$.]