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Material that should be known for the final

1. Theoretical derivation of the regression coefficient (vector) and its variance.

2. Working with numerical examples—the linear model with 2 regressors will often be used in midterm/exam questions, I may give you some numbers and you should be able to find, say the coefficient and the standard errors.

3. The Frisch-Waugh theorem and applications. I may ask you to prove the FW theorem, so make sure you are comfortable working with the projection matrix $P_X = X\,(X'X)^{-1}X'$ and the residual maker $M_X = I - P_X = I - X\,(X'X)^{-1}X'$

4. R^2, adjusted R^2, and partial R^2

5. the t- and F-test and the Chow-test (and similar simple applications of the F-test that I may think of). Confidence intervals.

6. Functional Form (as I covered it in class: dummy variables, interactions, elasticities, semi-log, etc.)

7. Data Problems (as I covered it in class: omitted variable bias, classical measurement error, multi-collinearity, Winsorizing, truncating (also called trimming) data)

8. Asymptotics. You will need to use the Law of Large Numbers (LLN) and the Central Limit Theorem (CLT), but I did not mention the explicit version of the LLN or the CLT, so you can talk about "the" LLN, and "the" CLT.

9. Consistency of OLS (assumptions needed on $X'X$ and explaining that $X'\epsilon$ is a sum of independent variables so that a LNN holds).

10. Convergence of the t-test to a standard normal. Convergence of the F-test to Chi-square test for $N \to \infty$.

11. GLS. Understand that if Ω is the variance matrix, one can choose a Cholesky factorization so that $\Omega^{-1/2}$ is lower triangular and multiplying the $n'th$ row with the true error vector corresponds to calculating $x_n - E(x_n|x_{n-1}, ...x_1)$ (and scaling with the standard error). Therefore the elements of $\Omega^{-1/2}e$ are i.i.d., which is equivalent to $var(\Omega^{-1/2}\,e) = \Omega^{-1/2}\,var(e)\,\Omega^{-1/2'} = \Omega^{-1/2}\,\Omega\,\Omega^{-1/2'} = I$. This got a little detailed, but you can take that as a reminder that formulas for the variance of matrix times a stochastic vector are essential for OLS/GLS theory.

12. Feasible GLS. Main examples: 1) autocorrelation in residuals 2) heteroskedasticity
13. White robust variance estimator. Explain why it works (under suitable assumptions).
14. Maximum Likelihood. Be able to show that $\hat{\beta}_{OLS} = \hat{\beta}_{ML}$ under the standard assumptions plus normality and explain the relation between are standard OLS estimate of the error variance and the ML estimate of the error variance. Also, be able to derive the ML estimator in the case of heteroskedasticity. (I won't ask for the case of autocorrelated residuals.)
15. The IV estimator when there are more instruments than regressors and the special case when the number of instruments is equal to the number of regressors.
16. Explain why the IV-estimator is consistent (and list the assumptions) but not unbiased. (Note: there isn't so much to remember about the assumptions, we basically assume "what we need" in order to get consistency.)