University of Houston **Bent E. Sørensen**
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Material for midterm

1. Matrix algebra. There are good introductions to this material in Davidson-MacKinnon and Greene (I like Greene's appendices better on this). I list some of the more important stuff below (although it is not exhaustive).

   - You are expected to know the basic rules about adding and multiplying etc. matrices before taking this class
   - Partitioned matrices are important in econometrics, so you have to able to invert and multiply those
   - A special case of writing a matrix in partitioned form is to write it as a collection of row vectors or a collection of column vectors. For the important issue of consistency of OLS, this is crucial.
   - You are expected to be able to find the determinant of a 2×2 matrix and matrices that are block-diagonal with 2×2 matrices or scalars along the diagonal.
   - You have to be able to diagonalize a symmetric matrix and you should know the role of the eigenvalues. You should be able to fine eigenvalue for 2×2 matrices. This includes the taking of the square root of a matrix and the square root of the inverse.
   - You should know about idempotent matrices and their eigenvalues (0 or 1).

2. Statistics

   - You should know the multivariate normal distribution and how it relates to the χ-square distribution.
   - You have to be comfortable taking means and variances of a stochastic vector (a vector of stochastic variables).
   - You should (absolutely) know what happens to the mean and variance of a stochastic vector if it is multiplied by a matrix.
   - You should be able to explain why $e'Me$ follows a χ-square distribution if M is idempotent and e is standard normal (and explain the degrees of freedom).
   - You have to know (for testing) that if X is $N(0, \Sigma)$ then $X'\Sigma^{-1}X$ is *chi*-square. This follows because $\sigma^{-.5}X$ is $N(0, I)$, you should be able to explain this, but the higher priority is to know the result for $X'\Sigma^{-1}X$ which is the multivariate equivalent of dividing by the standard error (if X is a scalar, then $X'\Sigma^{-1}X$ is X^2/σ^2.

3. Theoretical derivation of the regression coefficient (vector) and its variance.
4. Be able to show the $\hat{\beta}$ (the estimated coefficient in the linear regression model under the standar assumptions [know what those are]) is unbiased. The unbiased estimator of the error variance.
5. 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.
6. The Frisch-Waugh (FM) 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 $M_X = I - P_X = I - X\,(X'X)^{-1}X'$ Important applications of the FM theorem are a) regressing on a large number of dummy variables, b) evaluating the marginal impact of an extra regressor, c) showing the bias from left-out variables, d) "added value plots" (to check for outliers).
7. R^2, adjusted R^2, and partial R^2
8. the t- and F-test (know how to formulat the test of hypothesis described in words and know the equivalence of the "goodness of fit" version and the version where you directly use $R\hat{\beta} - q$ know how to prove that the F- and t-tests follow the t- and F-distributions). The Chow-test (and similar simple applications of the F-test that I may think of). Confidence intervals.
9. Functional Form (as I covered it in class: dummy variables, interactions, elasticities, semi-log, etc.)
10. Data issues: Classical measurement error, multi-collinearity
11. 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.