ECON 7331 — ECONOMETRICS I

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Hours: You can usually drop by anytime, sometimes I am out Thursday-Friday and sometimes I work at home in the morning, so email for an appointment if you want to be sure (emailing about appointments is the best way, because I use my inbox to keep track of appointments).
Obligatory Notices:
Students with Disabilities: The University of Houston System complies with Section 504 of the Rehabilitation Act of 1973 and the Americans with Disabilities Act of 1990, pertaining to the provision of reasonable academic adjustments/auxiliary aids for students with a disability. In accordance with Section 504 and ADA guidelines, the University of Houston strives to provide reasonable academic adjustments/auxiliary aids to students who request and require them. Students seeking accommodation in this course should contact the instructor after obtaining the appropriate documentation through the UH Center for Students with Disabilities.

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`http://www.uh.edu/caps/outreach/lets_talk.html`

Learning Outcomes:

- Students will learn, through lectures, homeworks, and TA-sessions, to master econometric tools at a level that, in conjunction with other core-classes, enables the students to perform statistical analysis of economic models.
- Students will develop their technical skills as a background for doing empirical work to the level expected in graduate economics programs. For this purpose, student will learn to use the econometric software to estimate models on actual economic data.
- Students will learn the basic ideas of advanced econometrics with a focus on empirically relevant issues.

Course Description

I list at the bottom of this file what I taught in the Spring of 2017. Each week we will post programs in Matlab. (Presonally, I am very experienced with Gauss but the TA master's Matlab and in any event matrix languages are quite similar so I can usually hep you). We might also use the Stata econometrics package, which is ubiquitous in applied microeconomics. Programming of econometric estimators (or rather adapting programs that I post) is an essential part of the class. The exams will include computer code (maybe with a line missing that you have to add [maybe in words]) so if you don't understand the code, you will be lost.

The topics you should know for the exam is what is taught in class. It is usually not helpful to read further material at this stage, but it is often very helpful to read an alternative presentation of the same material. Even undergraduate texts, which do not use matrix algebra, may be helpful in getting a better feeling for various tools.

Readings:

Textbooks:

I plan to use Davidson and MacKinnon: "Econometric Theory and Methods" Oxford University Press 2004 and Econometric Analysis, William H. Greene, 7th Edition, Prentice Hall, 2012 (this book is among the 100 all-time most cited books in the world according to Prof. Greene's web-site). I may also post some supplementary papers or links and some notes of my own but, again, you are supposed to know all that has been taught in class and nothing more. I find Davidson and MacKinnon more to the point, but if you prefer many examples, there are more in Greene (but I think often that makes it easier to get lost, but we are all different). Personally, I also like Goldberger: A course in Econometrics, which is really to the point, but it is a bit old now. I will assume you have access to Davidson-MacKinnon and Green and will often post homeworks from these books.

Notes Notes, homeworks, information, etc. will be posted on the class web-page. The class web-page will be accessible from my home page.

Material covered last year (this is all standard stuff and this will be covered again—we may cover a little more or less. Some of the material near the end are given a more introductory treatment and we will return to it in Econometrics II:

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).

   (a) You are expected to know the basic rules about adding and multiplying etc. matrices before taking this class.

   (b) Partitioned matrices are important in econometrics, so you have to able to invert and multiply those.

   (c) 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.

(d) 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.

(e) You have to be able to diagonalize a symmetric matrix and you should know the role of the eigenvalues (More often, though, you will need to make a theoretical argument relying on the existence of a diagonalization, as opposed to doing it numerically). You should be able to find eigenvalue for 2×2 matrices. This includes the taking of the square root of a matrix and the square root of the inverse.

(f) You should know about idempotent matrices and their eigenvalues (0 or 1).

2. Statistics

   (a) You should know the multivariate normal distribution and how it relates to the χ-square distribution.

   (b) You have to be comfortable taking means and variances of a stochastic vector (a vector of stochastic variables).

   (c) You should (absolutely) know what happens to the mean and variance of a stochastic vector if it is multiplied by a matrix.

   (d) 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).

   (e) You have to know (for testing) that if X is $N(0, \Sigma)$ then $X'\Sigma^{-1}X$ is χ-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 $X^2/\sigma^2 = (X/\sigma)^2$, i.e., the square of standard normal.

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 standard assumptions [know what those are]) is unbiased. The unbiased estimator of the error variance (be able to prove that it is unbiased).

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) Showing the bias in the case of omitted (left-out) variables.

   (c) Evaluating the marginal impact of an extra regressor.

(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.

    (a) Consistency of the OLS estimator (know the assumptions needed on $X'X$ and be able to explain that $X'\epsilon$ is a sum of independent variables so that a LNN holds).

    (b) Consistency of the variance estimator.

    (c) Convergence of the $t-$ test to a Normal test (whether the data are Normally distributed or not, as long a CLT holds).

    (d) Asymptotic χ^2-test of restrictions even if the errors are not Normally distributed (the case where they are, is of course a special case, so this implies that the standard F-test converges to the χ^2-test (and the F-distribution to the χ^2-distribution.

12. 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). (Confer point 2e.) 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.

13. Feasible GLS. Main examples: 1) autocorrelation in residuals 2) heteroskedasticity

14. White robust variance estimator. Explain why it works (under suitable assumptions).

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.)

17. Maximum Likelihood.

   (a) 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.

   (b) Also, be able to derive the (Normal) ML estimator in the case of heteroskedasticity. (I won't ask for the case of autocorrelated residuals.)

   (c) Know the Cramer-Rao lower bound—in particular, that the inverse information matrix is the asymptotic variance of the estimator.

   (d) Be able to prove the information matrix equality (maybe for a particular simple likelihood function).

   (e) Be able to find the ML estimator for simple distributions such as exponential, log-normal, Bernoulli.