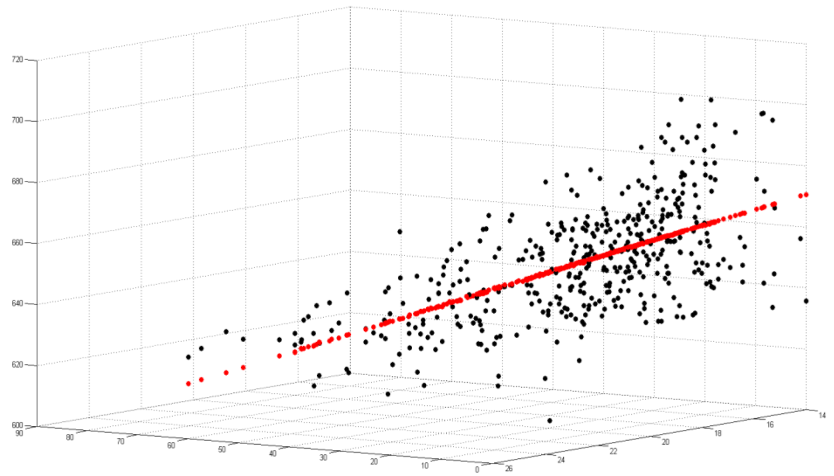
EC 3303: Econometrics I

Assessing Regression-Based Studies



Kelvin Seah

AY 2022/2023, Semester 2

Outline

1. Framework for Assessing Regression Studies

2. Threats to Internal Validity

3. External Validity

Assessing Studies Based on Multiple Regression

- What makes a study that uses multiple regression reliable or unreliable?

- Is there a systematic way to assess (critique) regression-based studies?

- Framework for assessing regression-based studies:

  - relies on the concepts of ***Internal*** & ***External Validity***.

Internal & External Validity

Internal Validity

- A study is internally valid if its statistical inferences about causal effects are valid for the population & setting studied.
  - where the "population studied" is the population of entities – people, firms, school districts, etc – from which the sample was drawn.
  - where "setting" refers to the institutional, social, economic environment.

External Validity

- A study is externally valid if its inferences can be generalised to other population & settings.

Is there a systematic way to assess regression studies?

- Can assess a study by asking:

  1) Is it plausibly internally valid?

    - Yes: Why might it be internally valid?
    - No: Why might internal validity be threatened?

  2) Can I generalise the inferences & conclusions from this study to other populations & settings?

    - Why or why not?

Regression Studies & Internal Validity

Multiple regression has some key virtues:

- It provides an estimate of the effect on Y arising from a change in X.
- It resolves the problem of omitted variable bias, ***if*** omitted variable(s) can be measured & included.
- It can handle nonlinear relationships.

Still, OLS might yield a *biased* estimator of the true *causal* effect – that is, it might not yield internally valid inferences…

Internal Validity

For a study to be internally valid, ***2 conditions*** must be met:

1) The ***estimator*** of the causal effect of interest should be ***unbiased*** and ***consistent.***

2) Hypothesis tests have the ***correct significance level***; confidence intervals have the ***correct confidence level*** (i.e. standard errors are correctly estimated).

In practice, these requirements might not be met, and this constitutes a threat to internal validity.

Threats to Internal Validity

- Omitted variable bias
- Wrong functional form
- Errors-in-variables bias
- Sample selection bias
- Simultaneous causality bias

All of these imply $E(u_i|X_{1i}, X_{2i}, \ldots, X_{ki}) \neq 0$

1. Omitted Variable Bias

Omitted variable bias arises if you omit from the regression a variable which is ***both*:**

(i) a determinant of Y ***&***

(ii) correlated with at least one included regressor.

We first discussed omitted variable bias in regression with a single X, but OV bias can arise when there are multiple X's as well.

What might we have omitted in testscore – class size regressions?

Potential Solutions to Omitted Variable Bias

If the omitted variable is observed

1. If you know what the omitted variable is, include it as an additional regressor in the multiple regression.

If the omitted variable is not observed

2. Use ***panel data*** to weed out the effects of unobserved omitted variables which do not change over time (EC3304).

If the omitted variable is not observed

3. Use ***instrumental variables (IV)*** regression (EC3304)

4. Use a randomized controlled experiment

- if the treatment X is randomly assigned, then X necessarily will be distributed independently of u.

- $E(u_i|X_i = x) = 0$

Project STAR

2. Incorrect Functional Form

- Bias can arise if the researcher wrongly specifies the functional form of the regression.

  - e.g.: if the true regression function is nonlinear in X (cubic) but the researcher estimates a linear regression, then the OLS estimator of the effect of X will be biased.

```
. regress  testscr avginc, robust

Linear regression                                      Number of obs =     420
                                                       F(  1,   418) =  273.29
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.5076
                                                       Root MSE      =  13.387

------------------------------------------------------------------------------
             |               Robust
     testscr |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      avginc |    1.87855   .1136349    16.53   0.000     1.655183    2.101917
       _cons |   625.3836   1.867872   334.81   0.000      621.712    629.0552
------------------------------------------------------------------------------

. regress testscr  avginc avginc2 avginc3, robust

Linear regression                                      Number of obs =     420
                                                       F(  3,   416) =  270.18
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.5584
                                                       Root MSE      =  12.707

------------------------------------------------------------------------------
             |               Robust
     testscr |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      avginc |   5.018677   .7073505     7.10   0.000      3.62825    6.409104
     avginc2 |  -.0958052   .0289537    -3.31   0.001    -.1527191   -.0388913
     avginc3 |   .0006855   .0003471     1.98   0.049     3.27e-06    .0013677
       _cons |    600.079   5.102062   117.61   0.000     590.0499     610.108
------------------------------------------------------------------------------
```

How does an increase in district income from $5,000 to $6,000 affect testscore?

- Linear Specification: increase testscore by 1.9 points

- (True) Cubic Specification: increase testscore by 4.0 points

Potential solutions to functional form misspecification

- use the "appropriate" nonlinear specifications (logarithms, polynomials, interactions)

3. Errors-in-Variables Bias

we have assumed that X's are measured without error.

- In reality, economic data often have measurement error.
- Data entry errors in administrative data.
- Recollection errors in surveys (monthly salary during your first year of work?)
- Ambiguous question problems (income last year?)
- Intentionally false response problems (How often do you drink and drive?)

Consequences of Measurement Error in a Regressor

Suppose we have a single regressor X_i (say, actual earnings):

- X_i is measured with error, as $\tilde{X}_i$ (respondent's reported earnings).
- because we observe $\tilde{X}_i$ (not X_i), the regression equation actually estimated will be the one based on $\tilde{X}_i$.

Suppose true model is:

$$Y_i = \beta_0 + \beta_1 X_i + u_i \quad (1)$$

and that $E(u_i|X_i) = 0$

Written in terms of $\tilde{X}_i$, (1) is

$$\begin{aligned} Y_i &= \beta_0 + \beta_1 \tilde{X}_i + \left[\beta_1\left(X_i - \tilde{X}_i\right) + u_i\right] \\ &= \beta_0 + \beta_1 \tilde{X}_i + v_i \qquad (2) \end{aligned}$$

where $v_i = \beta_1(X_i - \tilde{X}_i) + u_i$

$$Y_i = \beta_0 + \beta_1\tilde{X}_i + \underbrace{[\beta_1(X_i - \tilde{X}_i) + u_i]}_{v_i}$$

- measurement error is $X_i - \tilde{X}_i$.
- If the measurement error $(X_i - \tilde{X}_i)$ is correlated with the measured value $\tilde{X}_i$, then $\tilde{X}_i$ will be correlated with the error term v_i, and $\hat{\beta}_1$ will be biased and inconsistent.
- The size & direction of the bias in $\hat{\beta}_1$ depends on the nature of the correlation between $\tilde{X}_i$ & the measurement error.

What would happen, if instead, Y is measured with some random error?

- Not much…$Var(\hat{\beta}_1)$ would be larger than if Y was not measured with error, but ***no bias*** would be induced in $\hat{\beta}_1$

true model:

$$Y_i = \beta_0 + \beta_1 X_i + u_i \quad (1)$$

Written in terms of the incorrectly measured variable, $\tilde{Y}_i$, (1) is

$$\tilde{Y}_i = \beta_0 + \beta_1 X_i + u_i + w_i \quad (3)$$

where w_i represents random measurement error.

$$\tilde{Y}_i = \beta_0 + \beta_1 X_i + \underbrace{u_i + w_i}_{v_i} \quad (3)$$

$$\tilde{Y}_i = \beta_0 + \beta_1 X_i + v_i \quad (4)$$

If the measurement error in Y , w_i, is random, then w_i is independently distributed of X_i.

- So $E(w_i|X_i) = 0$, and in which case, $E(v_i|X_i) = 0$.
- $\hat{\beta}_1$ is unbiased.

Potential Solutions to Errors-in-Variables Bias

1) Obtain better data; get more accurate measures of X.

2) Use instrumental variables regression (EC3304)

- Involves searching for a variable (“instrumental” variable) that is correlated with the actual value X_i but is uncorrelated with the measurement error.

4. Sample Selection Bias

- So far, we have assumed simple random sampling of the population.
- In some cases, simple random sampling is thwarted because the dependent variable is observed only for a restricted (non-random) sample.

Example: Returns to Education

What is the return to an additional year of education?

Empirical strategy:

- Sampling scheme: simple random sample of employed workers (employed, so we have wage data).
- Data: earnings & years of education.
- regress ln(*earnings*) on *years_education.*
- Ignoring issues of omitted variable bias and measurement error for now – is there bias?

$$ln(Earnings_i) = \beta_0 + \beta_1 Years\_Educ_i + u_i$$

- We want to know how an additional year of schooling affects earnings for the ***population of workers***.
- However, (positive) earnings are only observed for employed workers.
- If we only sample employed workers and run the regression on this sample, $\hat{\beta}_1$ will be biased.
- because the effect on earnings of an additional year of schooling for employed workers does not give a reliable estimate of what the effect of an additional year of schooling would have been for unemployed workers had they been employed.

$$ln(Earnings_i) = \beta_0 + \beta_1 Years\_Educ_i + u_i$$

- Being in the sample means that you are employed.
- But employed and unemployed are likely to be different.
- Effect of an additional year of schooling for those employed might not represent the effect of an additional year of schooling for workers in general.

Potential Solution to Sample Selection Bias

- Collect the sample in a way that avoids non-random sample selection:

  - *Returns to education example*: random sample of all workers (including the unemployed).

5. Simultaneous Causality Bias

- we have assumed that ***X* causes *Y***.
- but what if ***Y* causes *X***, too?
- If so, there is ***simultaneous causality*** & the OLS estimator will be picking up ***both effects***.
  - OLS estimator will be biased & inconsistent.

Example: Class size effect

- Low *STR* results in higher test scores.
- But, suppose that as a result of a political process: districts with low test scores are given extra resources to lower *STR*
  - then low test scores would result in low *STR*
- What does this mean for a regression of *TestScore* on *STR*?

(a) Causal effect of X on Y :

$$Y_i = \beta_0 + \beta_1 X_i + u_i$$

(b) Causal effect of Y on X :

$$X_i = \gamma_0 + \gamma_1 Y_i + v_i$$

- fall in u_i means fall in Y_i,
  - if $\gamma_1 > 0$, this *implies* fall in $X_{i.}$
- So $Corr(u_i, X_i) \neq 0\ldots$
- …and $\hat{\beta}_1$ is biased and inconsistent.

$$Y_i = \beta_0 + \beta_1 X_i + u_i$$

$$X_i = \gamma_0 + \gamma_1 Y_i + vi$$

- What is the sign of $Corr(u_i, X_i)$ here?

a. +

b. -

Potential Solutions to Simultaneous Causality Bias

- Randomized controlled experiment:
  - negates feedback from Y to X.
- Use instrumental variables regression

Back to our Assessment

Kids with tuition fare worse

Analysis of Pisa data throws up surprising results for S'pore parents paying high tuition rates to help their children do well at school

Back in the 1990s, when I was a secondary school student, only a few of my friends had access to private tuition. Today, however, it is not uncommon for the majority of one's classmates to have this. Some may even have tuition in several subjects.

rates tend to be high in countries where high-stakes exams prevail because parents see a need to prepare their children adequately for these assessments.

Because performance in exams such as the Primary School Leaving Examination, O and A levels plays an important role in determining admissions to selective schools and universities, it is not surprising that parents in Singapore focus a lot of attention on programmes they perceive will ensure their children's academic success.

So the growing prevalence of

- Does having tuition cause kids to do worse?
- Y: TestScore
- X: tuition dummy, age, gender, home language, nativity, number of people at home, parents' education, parents' employment status
- Could there still be omitted variables that could result in OVB?

Back to our Assessment

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So the growing prevalence of

- Reverse Causality?
- Could test scores affect whether one enrolls in tuition?

Regression Studies & External Validity

- Whether one can generalise the results found in a study to other population & settings depends on how similar the populations and settings are.

- Can we generalise the class size results from California elementary school districts (in 1999) to:

  - Massachusetts elementary school districts in 1999?

  - Californian elementary school districts in 2015?

  - Californian universities in 1999?

  - Singapore elementary schools in 2015?

Are Results of Fertility Studies done on the Nordic Countries Generalisable to Singapore?

- Experiences of Nordic countries show that pro-parenthood measures (financial support , leave provisions) lead to increases in fertility rates.

- Why aren't pro-parenthood policies working in Singapore?

- Differences in settings? Cultural norms?

Class Size Effect

- Long history of conflicting findings.

ASK: NUS Economists

Reducing class size is good, but mind the costs

Kelvin Seah
Kah Cheng

For The Straits Times

Q *Does class size matter?*

A Earlier this year, the issue of whether to implement smaller class sizes in Singapore schools was hotly debated in Parliament. Some felt that the current class size

the data collected by researchers for this purpose is problematic because it is based on observations. In such settings, students are not randomly assigned to different classes. So students from larger classes and those from smaller ones tend to be dissimilar.

For instance, in Singapore schools, less able students may be assigned to smaller classes (students enrolled in learning support programmes, for instance) while more able students are assigned to the regular larger

Other scholars later found that Mr Hanushek's conclusions might have been misguided because not all the estimates included in his meta-analysis were equally reliable. Many of the estimates were based on research designs – like regressions – which would not have allowed for credible estimation of the class size effect.

More recent reviews of the literature, conducted for instance, by Northwestern University's Professor Diane Schanzenbach, focused on studies based on

Joshua Angrist and co-researcher Victor Lavy.

Both studies show that smaller classes are effective in raising student achievement, and that the benefits of attending a smaller class are greater for students from low-income families.

Even though reducing class size may improve student learning, it does not mean that Singapore should necessarily go ahead with it. Reducing class size comes at a substantial cost. More teachers need to be hired. And if schools are

California Class Size Effect

- We found evidence that reductions in class size improve test scores in California.

    - i.e. class size has a ***statistically significant*** effect on test scores

- But does class size have a ***practically important*** effect on test scores?

For simplicity, consider estimates from linear regressions again…

TABLE 7.1 Results of Regressions of Test Scores on the Student–Teacher Ratio and Student Characteristic Control Variables Using California Elementary School Districts

Dependent variable: average test score in the district.

Regressor	(1)	(2)	(3)	(4)	(5)
Student–teacher ratio (X_1)	−2.28** (0.52)	−1.10* (0.43)	−1.00** (0.27)	−1.31** (0.34)	−1.01** (0.27)
Percent English learners (X_2)		−0.650** (0.031)	−0.122** (0.033)	−0.488** (0.030)	−0.130** (0.036)
Percent eligible for subsidized lunch (X_3)			−0.547** (0.024)		−0.529** (0.038)
Percent on public income assistance (X_4)				−0.790** (0.068)	0.048 (0.059)
Intercept	698.9** (10.4)	686.0** (8.7)	700.2** (5.6)	698.0** (6.9)	700.4** (5.5)
Summary Statistics					
SER	18.58	14.46	9.08	11.65	9.08
$\bar{R}^2$	0.049	0.424	0.773	0.626	0.773
n	420	420	420	420	420

These regressions were estimated using the data on K-8 school districts in California, described in Appendix 4.1. Standard errors are given in parentheses under coefficients. The individual coefficient is statistically significant at the *5% level or **1% significance level using a two-sided test.

```
. summarize  str, detail

                             str
-------------------------------------------------------------
      Percentiles      Smallest
 1%     15.13898             14
 5%     16.41658       14.20176
10%     17.34573       14.54214       Obs                 420
25%     18.58179       14.70588       Sum of Wgt.         420

50%     19.72321                      Mean           19.64043
                        Largest       Std. Dev.      1.891812
75%     20.87183          24.95
90%     21.87561       25.05263       Variance       3.578952
95%     22.64514       25.78512       Skewness      -.0253655
99%     24.88889           25.8       Kurtosis       3.609597
```

```
. summarize testscr, detail

                           testscr
-------------------------------------------------------------
      Percentiles      Smallest
 1%       612.65         605.55
 5%       623.15         606.75
10%      630.375            609       Obs                 420
25%          640          612.5       Sum of Wgt.         420

50%       654.45                      Mean           654.1565
                        Largest       Std. Dev.      19.05335
75%      666.675          699.1
90%        679.1          700.3       Variance       363.0301
95%        685.5          704.3       Skewness       .0916151
99%       698.45         706.75       Kurtosis       2.745712
```

The End?

The module may be over, but there are still important issues to be addressed:

- How to handle (*i*) omitted variables that are not observable, (*ii*) measurement errors, (*iii*) simultaneous causality? (IV estimation, panel data)
- What if my dependent variable is binary? (logit/probit regression)
- How do I forecast inflation, interest rates etc.? (time series analysis)
- Answering the above questions requires further modification of regression techniques – tune in to Econometrics II and III to find out how!

Consultations plus Additional Consultations

- Please do approach me if you have any queries on the class material.
- My Friday (4pm-6pm) consultation sessions for this week remain unchanged.
- However, for next week, consultations will be held on 20 April (Thursday), 4pm-6pm instead of the usual Friday slot because of the end-of-semester Economics Department meeting will be held at that time.
- To better support you for your final exam revisions, I will also be setting up an additional consultation session on 26 April (Wednesday), 4pm-6pm.
- Consultations will be done through Zoom through the usual link:

https://nus-sg.zoom.us/j/83502944248?pwd=K2c1WENobVBXV0YrcEliUlh4Z2s5dz09

Meeting ID: 835 0294 4248

Passcode: 714459

Reminder: Homework 2

- 11 Apr (12pm) - 14 Apr (7pm)

- Done through the “Canvas Quiz” Platform

- To access Homework 2, log on to Canvas

- Then on the left panel, click on “Quizzes” and you will be able to access the Homework.

- 20 MCQ questions

Final Exam

April 27^{th}, Thursday, 5pm-7pm (2hrs)

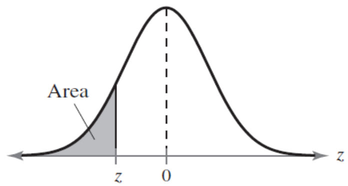
- Multi-part Short Answer Questions
- Closed book
- Coverage: All lectures
- Have a calculator with you
- Have your matric card with you
- Normal and F Tables can soon be found in Canvas under "Files" → "Supporting Materials for Final Exam (27 Apr, 5pm-7pm)"
- Venue: See next slide

Date	**Topic**	**Chapters (Stock and Watson)**
Week 1	Introduction and Overview	SW: Ch. 1
Week 2	Bivariate Linear Regression (I)	SW: Ch. 4
Week 3	Bivariate Linear Regression (II)	SW: Ch. 4,5
Week 4	Bivariate Linear Regression (III)	SW: Ch. 5
Week 5	Multiple Regression (I)	SW: Ch. 6
Week 6	Multiple Regression (II)	SW: Ch. 6,7
Week 7	Multiple Regression (III)	SW: Ch. 7
Week 8	**Midterm Test: (No lecture this week)**	
Week 9	Nonlinear Regression Functions (I)	SW: Ch. 8
Week 10	Nonlinear Regression Functions (II)	SW: Ch. 8
Week 11	Fixed Effects Regression	SW: Ch. 10
Week 12	Instrumental Variables Regression	SW: Ch. 12
Week 13	Assessment of Regression-based Studies and Conclusion	SW: Ch. 9

Venue for EC3303 final exam

- Students will soon be able to check the venue at Education Records System (EduRec)
- My Homepage > Academics > Examinations
- Click ‘View Exam Schedule’ and select ‘2022/2023 Semester 2’

Normal Table



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–3.2	.0005	.0005	.0005	.0006	.0006	.0006	.0006	.0006	.0007	.0007
–3.1	.0007	.0007	.0008	.0008	.0008	.0008	.0009	.0009	.0009	.0010
–3.0	.0010	.0010	.0011	.0011	.0011	.0012	.0012	.0013	.0013	.0013
–2.9	.0014	.0014	.0015	.0015	.0016	.0016	.0017	.0017	.0018	.0019
–2.8	.0019	.0020	.0021	.0021	.0022	.0023	.0023	.0024	.0025	.0026
–2.7	.0026	.0027	.0028	.0029	.0030	.0031	.0032	.0033	.0034	.0035
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–2.4	.0064	.0066	.0068	.0069	.0071	.0073	.0075	.0078	.0080	.0082
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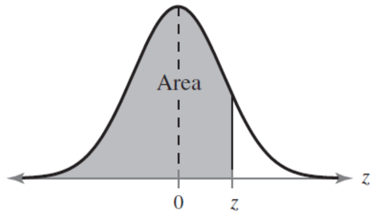
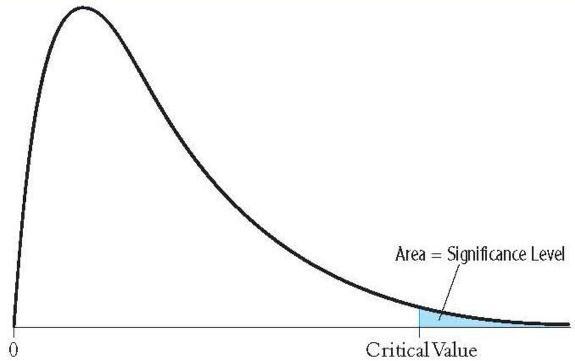
–1.9	.0233	.0239	.0244	.0250	.0256	.0262	.0268	.0274	.0281	.0287
–1.8	.0294	.0301	.0307	.0314	.0322	.0329	.0336	.0344	.0352	.0359
–1.7	.0367	.0375	.0384	.0392	.0401	.0409	.0418	.0427	.0436	.0446
–1.6	.0455	.0465	.0475	.0485	.0495	.0505	.0516	.0526	.0537	.0548
–1.5	.0559	.0571	.0582	.0594	.0606	.0618	.0630	.0643	.0655	.0668
–1.4	.0681	.0694	.0708	.0722	.0735	.0749	.0764	.0778	.0793	.0808
–1.3	.0823	.0838	.0853	.0869	.0885	.0901	.0918	.0934	.0951	.0968
–1.2	.0985	.1003	.1020	.1038	.1056	.1075	.1093	.1112	.1131	.1151
–1.1	.1170	.1190	.1210	.1230	.1251	.1271	.1292	.1314	.1335	.1357
–1.0	.1379	.1401	.1423	.1446	.1469	.1492	.1515	.1539	.1562	.1587
–0.9	.1611	.1635	.1660	.1685	.1711	.1736	.1762	.1788	.1814	.1841
–0.8	.1867	.1894	.1922	.1949	.1977	.2005	.2033	.2061	.2090	.2119
–0.7	.2148	.2177	.2206	.2236	.2266	.2296	.2327	.2358	.2389	.2420
–0.6	.2451	.2483	.2514	.2546	.2578	.2611	.2643	.2676	.2709	.2743
–0.5	.2776	.2810	.2843	.2877	.2912	.2946	.2981	.3015	.3050	.3085
–0.4	.3121	.3156	.3192	.3228	.3264	.3300	.3336	.3372	.3409	.3446
–0.3	.3483	.3520	.3557	.3594	.3632	.3669	.3707	.3745	.3783	.3821
–0.2	.3859	.3897	.3936	.3974	.4013	.4052	.4090	.4129	.4168	.4207
–0.1	.4247	.4286	.4325	.4364	.4404	.4443	.4483	.4522	.4562	.4602
–0.0	.4641	.4681	.4721	.4761	.4801	.4840	.4880	.4920	.4960	.5000



z	.00	.01	.02	.03	.04	.05	.06	.07	.08	.09
0.0	.5000	.5040	.5080	.5120	.5160	.5199	.5239	.5279	.5319	.5359
0.1	.5398	.5438	.5478	.5517	.5557	.5596	.5636	.5675	.5714	.5753
0.2	.5793	.5832	.5871	.5910	.5948	.5987	.6026	.6064	.6103	.6141
0.3	.6179	.6217	.6255	.6293	.6331	.6368	.6406	.6443	.6480	.6517
0.4	.6554	.6591	.6628	.6664	.6700	.6736	.6772	.6808	.6844	.6879
0.5	.6915	.6950	.6985	.7019	.7054	.7088	.7123	.7157	.7190	.7224
0.6	.7257	.7291	.7324	.7357	.7389	.7422	.7454	.7486	.7517	.7549
0.7	.7580	.7611	.7642	.7673	.7704	.7734	.7764	.7794	.7823	.7852
0.8	.7881	.7910	.7939	.7967	.7995	.8023	.8051	.8078	.8106	.8133
0.9	.8159	.8186	.8212	.8238	.8264	.8289	.8315	.8340	.8365	.8389
1.0	.8413	.8438	.8461	.8485	.8508	.8531	.8554	.8577	.8599	.8621
1.1	.8643	.8665	.8686	.8708	.8729	.8749	.8770	.8790	.8810	.8830
1.2	.8849	.8869	.8888	.8907	.8925	.8944	.8962	.8980	.8997	.9015
1.3	.9032	.9049	.9066	.9082	.9099	.9115	.9131	.9147	.9162	.9177
1.4	.9192	.9207	.9222	.9236	.9251	.9265	.9278	.9292	.9306	.9319
1.5	.9332	.9345	.9357	.9370	.9382	.9394	.9406	.9418	.9429	.9441
1.6	.9452	.9463	.9474	.9484	.9495	.9505	.9515	.9525	.9535	.9545
1.7	.9554	.9564	.9573	.9582	.9591	.9599	.9608	.9616	.9625	.9633
1.8	.9641	.9649	.9656	.9664	.9671	.9678	.9686	.9693	.9699	.9706
1.9	.9713	.9719	.9726	.9732	.9738	.9744	.9750	.9756	.9761	.9767
2.0	.9772	.9778	.9783	.9788	.9793	.9798	.9803	.9808	.9812	.9817
2.1	.9821	.9826	.9830	.9834	.9838	.9842	.9846	.9850	.9854	.9857
2.2	.9861	.9864	.9868	.9871	.9875	.9878	.9881	.9884	.9887	.9890
2.3	.9893	.9896	.9898	.9901	.9904	.9906	.9909	.9911	.9913	.9916
2.4	.9918	.9920	.9922	.9925	.9927	.9929	.9931	.9932	.9934	.9936
2.5	.9938	.9940	.9941	.9943	.9945	.9946	.9948	.9949	.9951	.9952
2.6	.9953	.9955	.9956	.9957	.9959	.9960	.9961	.9962	.9963	.9964
2.7	.9965	.9966	.9967	.9968	.9969	.9970	.9971	.9972	.9973	.9974
2.8	.9974	.9975	.9976	.9977	.9977	.9978	.9979	.9979	.9980	.9981
2.9	.9981	.9982	.9982	.9983	.9984	.9984	.9985	.9985	.9986	.9986
3.0	.9987	.9987	.9987	.9988	.9988	.9989	.9989	.9989	.9990	.9990
3.1	.9990	.9991	.9991	.9991	.9992	.9992	.9992	.9992	.9993	.9993
3.2	.9993	.9993	.9994	.9994	.9994	.9994	.9994	.9995	.9995	.9995
3.3	.9995	.9995	.9995	.9996	.9996	.9996	.9996	.9996	.9996	.9997
3.4	.9997	.9997	.9997	.9997	.9997	.9997	.9997	.9997	.9997	.9998

F Table



	Significance Level		
Degrees of Freedom	10%	5%	1%
1	2.71	3.84	6.63
2	2.30	3.00	4.61
3	2.08	2.60	3.78
4	1.94	2.37	3.32
5	1.85	2.21	3.02
6	1.77	2.10	2.80
7	1.72	2.01	2.64
8	1.67	1.94	2.51
9	1.63	1.88	2.41
10	1.60	1.83	2.32
11	1.57	1.79	2.25
12	1.55	1.75	2.18
13	1.52	1.72	2.13
14	1.50	1.69	2.08
15	1.49	1.67	2.04
16	1.47	1.64	2.00
17	1.46	1.62	1.97
18	1.44	1.60	1.93
19	1.43	1.59	1.90
20	1.42	1.57	1.88
21	1.41	1.56	1.85
22	1.40	1.54	1.83
23	1.39	1.53	1.81
24	1.38	1.52	1.79
25	1.38	1.51	1.77
26	1.37	1.50	1.76
27	1.36	1.49	1.74
28	1.35	1.48	1.72
29	1.35	1.47	1.71
30	1.34	1.46	1.70

This table contains the 90th, 95th, and 99th percentiles of the $F_{m,\infty}$ distribution. These serve as critical values for tests with significance levels of 10%, 5%, and 1%.

How to prepare for Final Exam?

- Read lecture notes carefully
    - Only material covered in lecture will be tested
- Practice HW and tutorial questions
- No need to memorize STATA commands, apart from those covered in the ***Lecture***