Advanced Econometrics

University of Warsaw

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Course information

- Prerequisites: probability, statistics, basic econometrics (regression analysis)
- Office hours: Monday 15.00-16.30 room 304 or online upon email request
- Requirements for passing the course:
  - written final exam
- Textbooks:
  - probability: B. Hansen (2022b). *Probability and Statistics for Economists*. Princeton University Press. ISBN: 9780691235943
  - econometrics: B. Hansen (2022a). *Econometrics*. Princeton University Press. ISBN: 9780691235899
  - Bayesian econometrics: G. Koop (2003). *Bayesian Econometrics*. Wiley. ISBN: 9780470845677
  - Data sets and codes for examples included in textbooks: `https://users.ssc.wisc.edu/~bhansen/econometrics/`

Econometric packages

- STATA:
  - not free, menu-driven, command-line, programming
  - available in computer labs and also you can obtain one year student license in the IT department
  - very good documentation with examples: `https://www.stata.com/features/documentation/`
  - video tutorials: `https://www.stata.com/links/video-tutorials/`
- R: `https://www.r-project.org/`
  - free, command line, programming (very limited GUI)
  - useful in spatial econometrics and in machine learning
- Python, package statsmodels `https://www.statsmodels.org/stable/index.html`
  - free, general programming
  - not as extensive as R and Stata
- Gretl: `https://gretl.sourceforge.net/`
  - free, easy to use, menu-driven
  - not as extensive as R and Stata

Trends in economic research

Sample: 748 articles published in the American Economic Review (AER), Journal of Political Economy (JPE), and Quarterly Journal of Economics (QJE)

TABLE 4
Percent Distributions of Methodology of Published Articles, 1963–2011 *

	Type of study				
Year	Theory	Theory with simulation	Empirical: borrowed data	Empirical: own data	Experiment
1963	50.7	1.5	39.1	8.7	0
1973	54.6	4.2	37.0	4.2	0
1983	57.6	4.0	35.2	2.4	0.8
1993	32.4	7.3	47.8	8.8	3.7
2003	28.9	11.1	38.5	17.8	3.7
2011	19.1	8.8	29.9	34.0	8.2

* A type could not be assigned to seventeen of the articles published in 1963.

Source: Hamermesh (2013)

Trends in economic research

Machine-learning-based classification of 134,892 papers published in 80 journals between 1980 and 2015

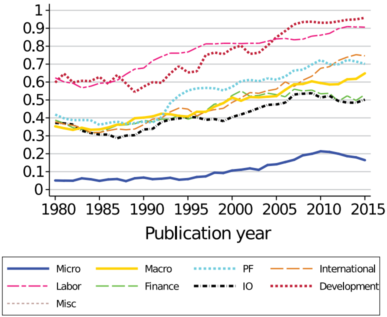

Figure 4. Weighted Fraction Empirical by Field

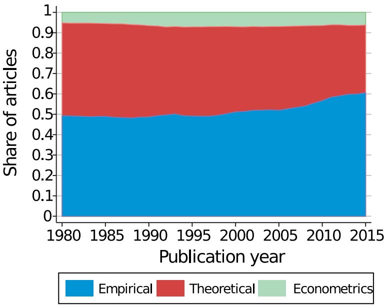

Figure 5. Publications by Style

Source: Angrist et al. (2017)

Weights are on the numbers of citations in top 6 journals

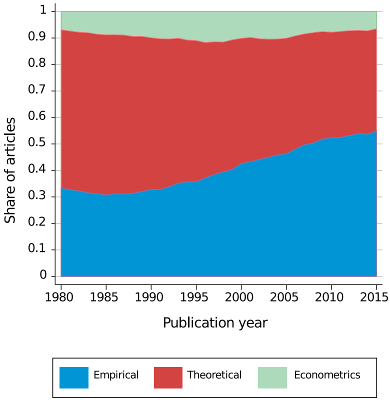

Figure 6. Weighted Publications by Style

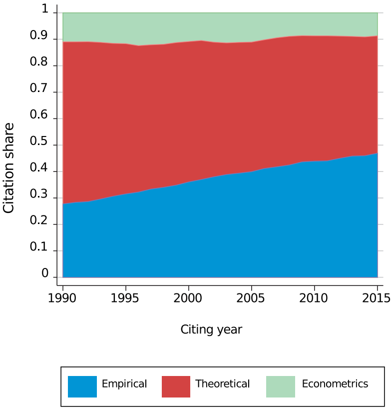

Figure 7. Weighted Citations by Style

Source: Angrist et al. (2017)

Replication crises

- In majority of cases in economics and in other sciences researchers are interested in cases when $\beta_j \neq 0$ - variable x_j influences the outcome variable y
- In such a case we are testing significance of of variable β_j by testing $H_0 : \beta_j = 0$ under $H_1 : \beta_j \neq 0$
- Rejection of H_0 and acceptance of H_1 of statistical significance of x_j is the desired result
- It is now well known that large proportion of studies (not only in economics) which have shown some statistically significant relationships failed to be replicated
- By replication we mean repeating the same study on different data set
- Why this is the case?

Positive predictive value

- John P A Ioannidis (2005) formulated simple formula which can help explain why large proportion of research findings are false.
- Assume that some proportion of tested hypotheses H_1 are valid. This proportion can be interpreted as unconditional probability that H_1 is true.
- If research hypothesis is credible than this probability is high.
- Denote $(H_1 : \mathit{true})$ as T, $(H_1 : \mathit{false})$ as F
- Positive result of the test (H_1 accepted) is denoted as P,
- Probability that H_1 is true given that H_1 was not rejected (Positive Predictive Value) is equal to:

$$\mathbb{P}(T|P) = \frac{\mathbb{P}(T \wedge P)}{\mathbb{P}(P)} = \frac{\mathbb{P}(P|T)\,\mathbb{P}[T]}{\mathbb{P}(P|T)\,\mathbb{P}[T] + \mathbb{P}(P|F)\,\mathbb{P}(F)}$$

$$= \frac{(1-\gamma)\,\mathbb{P}(T)}{(1-\gamma)\,\mathbb{P}(T) + \alpha\,(1-\mathbb{P}(T))}$$

Positive predictive value

- The positive predictive value can be interpreted as the percentage of research findings which are indeed true.
- Notice that it depends on γ (type 2 error prob.) but also on $\mathbb{P}(T)$ and α (type 1 error prob.)
- Example:
  - $\mathbb{P}(T) = \frac{1}{2}$ (50% hypothesis tested are valid), conventional $\gamma = 0.2$ (power 80%), $\alpha = 0.05$: $PPV = 0.94$
  - $\mathbb{P}(T) = 0.3$ (30% hypothesis tested are valid), underpowered $\gamma = 0.8$ (power 20%), $\alpha = 0.05$: $PPV = 0.63$
- John P A Ioannidis (2005) suggested as well that some positive test results are due to undetected mistakes in the research procedure. If the proportion of such results is u then

$$\mathbb{P}(T|P) = \frac{(1-(1-u)\gamma)\,\mathbb{P}(T)}{(1-(1-u)\gamma)\,\mathbb{P}(T) + ((1-u)\alpha + u)(1-\mathbb{P}(T))}$$

- Example:
  - $\mathbb{P}(T) = 0.3$ (30% hypothesis tested are valid), underpowered $\gamma = 0.8$ (power 20%), $\alpha = 0.05$, $u = 0.1$: $PPV = 0.45$

Meta-analysis of power in economic research

- The main problem with measuring power is that the β effect size is unknown
- However, if the multiple studies were published estimating the same β then it can be estimated as the (weighted) average $\overline{\beta}$ of the estimates published
- The power of individual studies can then be estimated by comparing the estimated standard errors with the estimate $\overline{\beta}$ of the effect β
- Such meta-analysis was done by John P. A. Ioannidis, Stanley, and Doucouliagos (2017) on the basis of 159 meta-analyses, 6730 primary articles and 64076 empirical estimates.
- Results suggest that in most of the research areas in economic the empirical studies are seriously underpowered and the estimates of the parameters are inflated

Estimated powers for articles in economics

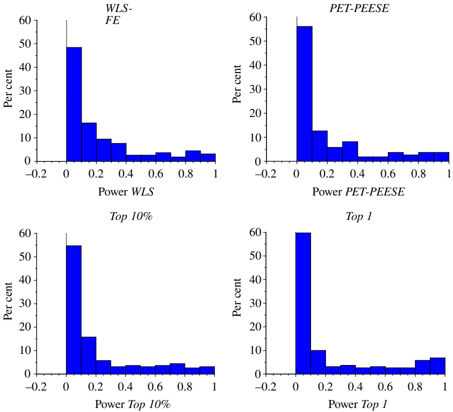

Fig. 1. Histograms of Adequately Powered Estimates in Empirical Economics
Note. Colour figure can be viewed at wileyonlinelibrary.com.

Source: John P. A. Ioannidis, Stanley, and Doucouliagos (2017)

Publication bias and p-hacking

- Journals seems to prefer articles with significant results - this is known as publication bias
- This creates adverse incentive for researchers to modify (possibly unconsciously) the methodology of the study so to obtain significant results
- The flexibility of definitions, the choice of estimation methods, the possible transformations of the data often make this practice possible
- Such a practice is known as data torturing and p-hacking
- HARKing (hypothesizing after results are known) - stating hypotheses after conducting research - affects $P(T)$

Publication bias and p-hacking

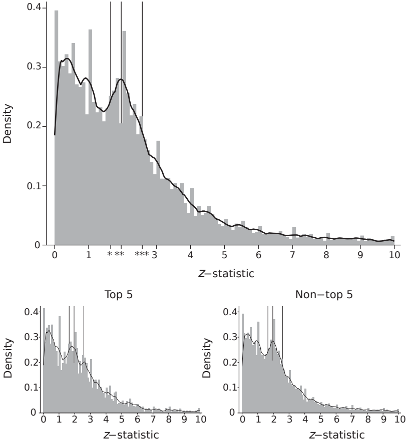

Figure 1. *z*-Statistics in 25 Top Economics Journals

Notes: The top panel displays histograms of test statistics for z ∈ [0, 10]. Bins are 0.1 wide. Reference lines are displayed at the conventional two-tailed significance levels. We have also superimposed an Epanechnikov kernel. The bottom left panel presents test statistics from the Top 5 journals (*American Economic Review, Econometrica, Journal of Political Economy, Quarterly Journal of Economics, and Review of Economic Studies*). The bottom right panel presents test statistics from the remainder of the sample. We do not weight articles.

Source: Brodeur, Cook, and Heyes (2020)

What determines the credibility of the studies

- John P A Ioannidis (2005) suggested that research findings are less likely to be true:
  - the smaller the sample used.
  - the smaller are the estimated effect β.
  - the greater the number and the lesser the selection of tested hypotheses.
  - the greater the flexibility in designs, definitions, outcomes, and analytical modes.
  - the greater the financial and other interests and prejudices.
  - the hotter the scientific field (with more scientific teams involved).

Solutions

- HARKing, data torturing
  - pre-registration: authors are required to preregister the study before the results are obtained, hypothesis, methods and variables must be defined before the study.
- Publication bias
  - replication studies: empirical studies which replicate original studies and are published even if results are negative
- p-hacking:
  - bayesian methods: in this kind of methods we do not use arbitrary significance levels when verifing hypotheses

Recommendations regarding the use of p-values

American Statistical Assosiation made the following recomandation on the use of the p-value in empirical research (Wasserstein and Lazar (2016)):

- P-values can indicate how incompatible the data are with a specified statistical model.
- P-values do not measure the probability that the studied hypothesis is true, or the probability that the data were produced by random chance alone.
- Scientific conclusions and business or policy decisions should not be based only on whether a p-value passes a specific threshold.
- Proper inference requires full reporting and transparency
- A p-value, or statistical significance, does not measure the size of an effect or the importance of a result.
- By itself, a p-value does not provide a good measure of evidence regarding a model or hypothesis.

Research procedure

- Formulate a hypothesis and explain why it is probable based on theory and other research.
- Collect a data set large enough to provide adequate power for statistical tests.
- Formulate a statistical model that is realistic, robust and allows you to verify your hypothesis.
- Estimate model parameters and perform statistical inference. Clearly explain data transformations and procedures used.
- Formulate conclusions and check whether changes in assumptions do not affect the results.

Objectives of empirical studies

- Why does modern economics rely so much on empirical research?
- Economic theory only provides qualitative guidance about the nature of relationships between variables.
- There are a number of cases where quantitative estimates are very important:
  - estimation of causal effect: policy analysis, evaluation studies
  - empirical verification of economic theory: statistical inference
  - forecasting

Examples of empirical questions

Example

What is the influence of the education on productivity?

Example

Is the supply of money money neutral in long-term?

Example

What will be the growth of GDP in the next quarter?

Economic model, statistical model, econometric model.

- Economic model: Cobb-Douglas production function

$$Q = AK^{\alpha}L^{\beta}$$

- Theory of economics implies: $\alpha > 0$, $\beta > 0$, if returns to scale are constat $\alpha + \beta = 1$
- Statistical model or Data Generating Model (DGP)

$$Q_t = A_t K_t^{\alpha} L_t^{\beta} e^{\varepsilon_t}$$

or in logarithms:

$$q_t = a_t + \alpha k_t + \beta l_t + \varepsilon_t$$

additional assumptions: $a_t = a + bt$, $\varepsilon_t \sim NID\left(0, \sigma^2\right)$

- Equation to be estimated

$$q_t = a + bt + \alpha k_t + \beta l_t + \varepsilon_t$$

- Estimated econometric model

$$q_t = \widehat{a} + \widehat{b}t + \widehat{\alpha}k_t + \widehat{\beta}l_t + \widehat{\varepsilon}_t$$

Types of econometric models.

- Structural: structure of the model is known, probabilistic elements fully specified, parameters are unknown
  - likelihood based analysis: Maximum Likelihood Estimation, Bayesian estimators
- Semiparametric: part of the probabilistic model is left unspecified
  - OLS, Generalised Method of Moments (GMM), semiparametric estimators
- Quasi-structural approach: model is treated as an approximation rather than truth
  - quasi-likelihood function, quasi-MLE
- Calibration approach: treat the models as approximations, rejects statistical methods of estimation,
  - uses *ad hoc* methods to fit models

Types of empirical data.

- Experimental: values of explanatory variables are determined by researcher and therefore can be treated as nonrandom
- Observational: neither explained nor explanatory variables are under control of researcher
- Most of the empirical data in economics is observational
- It is difficult to infer the causal mechanism from observational data as we cannot manipulate one variable to see the effect of these changes on other variables.
- What we are observing in practice are co-movements (correlations) of the observed variables
- However: co-movements (correlations) do not imply causality!

Standard data structures.

- Cross-section: observations independent, large number of observations
  - Example: Labor Force Survey (LFS)
- Time-series: serial dependence, sampling freqency often low (annual, quarterly), number of observations low
  - Example: GDP, interest rates
- Panel: for individual units data is collected for several time periods, combines characteristics of the cross-section and time-series data
  - Example: Panel Study of Income Dynamics (PSID)
- Clustered: observation within clusters are dependent, but between clusters observations are independent
  - households data
- Spatial: observations are dependent but nature of dependence is known and related to distance
  - Example: regional data

The Probability approach in econometrics

- Deterministic models cannot precisely describe empirical data in economics
- It is obvious that there are random factors influencing actions of economic agents
- On the other hand, economic agents, when making decisions, are taking into account random factors
- Therefore, models used in analysis of empirical data should explicitly include random elements
- Models used in empirical analysis of the data should then be probabilistic

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