Hertie School **Master of International Affairs/Master of Public Policy**
Spring Semester 2021
Course Syllabus, Version 01.02.2021

GRAD-C6-2001 Statistics II: Statistical Modeling and Causal Inference with R

Simon Munzert

1. General information

Class times	Group A: Tue, 10-12h Group B: Tue, 14-16h
Course Format	This course uses a "flipped classroom" format and combines 50 minutes of pre-recorded material (audio or video) with a 50-minute interactive seminar. Students will use the pre-recorded material to prepare for the lecture. The lecture is taught online via the platform Clickmeeting. Clickmeeting allows for interactive, participatory seminar style teaching.
Instructor	Prof. Dr. Simon Munzert
Instructors' offices	3.13.1
Instructors' e-mail	munzert@hertie-school.org
Instructors' phone numbers	+49 (0)30 259 219 450
Assistants	– Lisa Oswald, l.oswald@phd.hertie-school.org – Sebastian Ramirez Ruiz, ramirez-ruiz@hertie-school.org
Instructors' Office Hours	Thursday, 2-3pm. Please email me in advance to make an appointment and to let me know what you would like to talk about.

Link to Module Handbook **MIA** and **MPP**
Link to **Study, Examination and Admission Rules**

Instructor Information:
Simon Munzert is Assistant Professor of Data Science and Public Policy at the Hertie School and member of the Hertie School Data Science Lab. His research interests include attitude formation in the digital age, public opinion, and the use of online data in social research. He received his Doctoral Degree in Political Science from the University of Konstanz.

TA information:
Lisa Oswald is pursuing a PhD in Governance at the Hertie School in Berlin. She graduated from the University of Oxford with a MSc degree in Social Data Science, and from the University of Kassel with a BSc and MSc degree in Psychology. She is interested in online

communication and deliberation, the public perception of climate change, political opinion formation and the emergence of collective behaviour.

Sebastian Ramirez Ruiz is a Research Associate to Prof. Simon Munzert. He holds a Master's of Public Policy from the Hertie School and B.A.s in Sociology and Political Science from Stony Brook University. His research interest lie at the intersection of public opinion, political communication, and behavior with an emphasis on quantitative methodological rigor.

2. Course Contents and Learning Objectives

Course contents:
This course continues the sequence in statistical modeling. Assuming prior knowledge in simple and multiple linear regression modelling, it introduces students to a new perspective on studying causes and effects in social science research. Based on a framework of causality, the course agenda covers various strategies to uncover causal relationships using statistical tools. We start with reflecting about causality, the ideal research design, and then learn to use a framework to study causal effects. Then, we revisit common regression estimators of causal effects and learn about their limits. Next, we will focus on matching, instrumental variables, difference-in-differences and fixed effects estimators, regression discontinuity designs, and techniques to explore moderated relationships. All classes divide time between theory and application.

Main learning objectives:
The goals are to (1) acquaint you with some of the most common statistical methods used to demonstrate causality, (2) enable you to implement these with statistical software, and (3) prepare you for Hertie's methods electives.

Software:
We will work with RStudio, RMarkdown, and Git/GitHub to implement and practice the learned techniques. It is assumed that you have some basic knowledge in using R from Statistics I. If not, we strongly encourage you to familiarize yourself with R prior to the course so to be able to focus on the substance of the course. A good introduction to the use of R can be found in the following textbooks:

1. Wickham, H., & Grolemund, G. (2017). *R for Data Science*. Available at: https://r4ds.had.co.nz/.
2. Larsen, E. G., & Fazekas, Z. (2019). *Quantitative Politics with R*. Available at: http://www.qpolr.com/.

In addition to these resources, I encourage you to consult one of the many online tutorials for R, such as those offered by *Coursera*, *edX*, or *Udemy*.

Teaching style:
Each session will consist of a pre-recorded lecture, which, alongside the course readings, serves to familiarize students with the session's topic. This is followed by interactive Q&A sessions with the lecturer during which core concepts are discussed and further clarified. For the discussion of exercises and their implementation in R, students will be enrolled in a small-group support lab session taught weekly by a teaching assistant.

Prerequisites:
Statistics I, basic command of R

Diversity Statement:
Science thrives on the diversity of ideas and opinions, so I try to represent this diversity in our course as well. In the choice of course readings, we strive to cover authors with a diversity of backgrounds as far as possible. During class sessions, I seek to create a trusting and inclusive atmosphere that allows students of all orientations and backgrounds to be comfortable and openly engage in discussions. The R community lives these values and I want you to become part of it. If you have any suggestions that contribute to this goal, I am always grateful for feedback.

3. Grading and Assignments

Grading is structured around 3 main groups of assignments, each roughly equally weighted.

Composition of Final Grade:

Assignment 1: Weekly take-home assignments	Deadline: *11:59 PM CET on the day before the lecture*	Submit via GitHub	40%
Assignment 2: In-class (or online) final exam	Deadline: *precise date to be confirmed – final exam week*	In class/online	25%
Assignment 3: Final replication task	Deadline: *22.12.2020, 11:59 PM CET*	Submit via GitHub	35%

Assignment Details

Assignment 1
This assignment comprises 8 take-home problem sets (the 7 best of which will be graded) that participants will have to work on. The problem sets refer to 1-2 data sets that are shared by the instructor. The assignment will have to be submitted as a RMarkdown file containing both R code and the participant's answers to the questions. The assignments will go live at the day of the lecture and have to be submitted until the day before the next lecture, i.e. you will have 7 days to work on them. Each of the seven best assignments has an equal weight in the final grade for this component. You are generally encouraged to study and learn to use the software together. However, each student must hand in individual assignments, which will be graded separately.

Assignment 2
The in-class final exam will be comprised of a set of multiple-choice theoretical questions that draw on the class readings along with a set of questions on applied statistical problems based on analysis output.

Assignment 3

As a final assignment, course participants are asked to replicate, check, and amend the analyses of an existing academic paper. The instructor will provide a small set of replication data sets, and their accompanying code and manuscript. Participants will be asked to re-run the analyses reported in the manuscript, as well as go beyond them, by exploring additional questions with the data. This assignment will draw on skills built up during the weekly assignments. The replication project will be brief (6-8 pages). However, please keep in mind that replicating and understanding code written by someone else takes considerable time.

Late submission of assignments: For each day an assignment is turned in late, the grade will be reduced by 10% (e.g. submission two days after the deadline would result in 20% lower grade). The deduction happens at the moment at which the deadline is passed (00:00 AM).

Attendance: Students are expected to be present and prepared for every class session. Active participation during seminar discussions is essential. If unavoidable circumstances arise which prevent attendance or preparation, the instructor should be advised by email with as much advance notice as possible. Please note that students cannot miss more than two out of 12 course sessions. For further information please consult the Examination Rules §10.

Academic Integrity: The Hertie School is committed to the standards of good academic and ethical conduct. Any violation of these standards shall be subject to disciplinary action. Plagiarism, deceitful actions as well as free-riding in group work are not tolerated. See Examination Rules §16.

Compensation for Disadvantages: If a student furnishes evidence that he or she is not able to take an examination as required in whole or in part due to disability or permanent illness, the Examination Committee may upon written request approve learning accommodation(s). In this respect, the submission of adequate certificates may be required. See Examination Rules §14.

Extenuating circumstances: An extension can be granted due to extenuating circumstances (i.e., for reasons like illness, personal loss or hardship, or caring duties). In such cases, please contact the course instructors and the Examination Office *in advance* of the deadline.

4. General Readings

Throughout the class we rely heavily on the material in:

- **Impact Evaluation**
  Gertler, P.J., Martinez, S., Premand, P., Rawlings, L.B., Vermeersch, M.J. (2016). Impact Evaluation in Practice. Second Edition. World Bank Group. Preprint available at https://openknowledge.worldbank.org/handle/10986/25030.
- **The Mixtape**
  Cunningham, S. (2021). Causal Inference: The Mixtape. New Haven: Yale University Press. Preprint available at: https://www.scunning.com/causalinference_norap.pdf
- **What if**
  Hernán, M. A., & Robins, J. A. (2020). *Causal Inference: What If*. Boca Raton, FL: CRC Press. Preprint available at: https://cdn1.sph.harvard.edu/wp-content/uploads/sites/1268/2019/10/ci_hernanrobins_10oct19.pdf.
- **Mastering Metrics**

Angrist, J. D., & Pischke, J.-S. (2015). *Mastering 'Metrics: The Path from Cause to Effect*. Princeton: Princeton University Press.

In addition, participants will encounter chapters from other books and journal articles to read; these primarily provide illustrations and more background. Articles that are designated as **Optional Readings** are not required, although references to them and techniques they use will be made during the lecture.

Articles listed under **Application Reading** serve as an example case during the lecture. It is mandatory to read them in advance.

This course has an exclusive focus on causal identification and inference. There are more books out there that people commonly consult to learn about these topics, including:

1. Angrist, Joshua David, and Jörn-Steffen Pischke. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton: Princeton University Press, 2009.
2. Pearl, J., & Mackenzie, D. (2018). *The Book of Why: The New Science of Cause and Effect*. New York: Basic Books.
3. Morgan, S. L., & Winship, C. (2015). *Counterfactuals and Causal Inference: Methods and Principles for Social Research* (2nd ed.). New York: Cambridge University Press.

Moreover, there are other books that focus more on statistical modeling and estimation. If you are interested in these topics, please consult the following:

1. Andrew G., & Hill, J. (2007). *Data Analysis Using Regression and Multilevel/Hierarchical Models*. New York: Cambridge University Press. [*a reference book for regression modeling and, particularly, mixed-effects models, from a Bayesian perspective*]
2. Enders, C. K. (2010). *Applied Missing Data Analysis*. New York: The Guilford Press. [*an accessible introduction into the problems of missing data for our analyses; includes chapters on maximum likelihood estimation*]
3. Fox, J. (2016). *Applied Regression Analysis and Generalized Linear Models* (3rd ed.). London: Sage Publications. [*theoretical treatment of OLS regression and GLMs, along with selected additional topics, e.g. multilevel models*]
4. Freedman, D. A. (2009). *Statistical Models: Theory and Practice*. Cambridge: Cambridge University Press.
5. Wooldridge, J. M. (2013). *Introductory Econometrics: A Modern Approach* (5th ed.). Mason, OH: Cengage Learning. [*an econometric classic*]

Finally, it's the 2020s and there are tons of video and audio resources around causal inference on the web. Here are some that I can recommend:

1. Causal Inference Bootcamp https://mattmasten.github.io/bootcamp/
2. Online Causal Inference Seminar https://sites.google.com/view/ocis/, https://www.youtube.com/channel/UCiiOj5GSES6uw21kfXnxj3A/videos
3. Causal Inference Podcast, https://casualinfer.libsyn.com/

5. Session Overview

Session	Session Date	Session Title
		FOUNDATIONS OF CAUSALITY
1	09.02.2021	Counterfactual causality
2	16.02.2021	The potential outcomes framework and experiments
3	23.02.2021	Causal graphs
		BASIC TOOLS FOR CAUSAL INFERENCE
4	02.03.2021	Regression estimators of causal effects
5	09.03.2021	Matching
6	16.03.2021	Instrumental variables
		Mid-term Exam Week: 22-26.03.2021 – no class
7	30.03.2021	Regression discontinuity designs
8	06.04.2021	Difference-in-differences and synthetic controls
9	13.04.2021	Panel data
		ADVANCED TOPICS
10	20.04.2021	Moderation and heterogeneous effects
11	27.04.2021	Validity and generalizability
12	04.05.2021	Developing, planning, and running evaluations
		Final Exam Week: 17-21.05.2021 – no class

6. Course Sessions and Readings

All readings that represent journal articles or select chapters from books will be available on the Moodle website. In the case of the Angrist & Pischke book, copyright law prevents us from making more than one chapter available on Moodle. I encourage participants to use the Hertie library or the other Berlin public libraries to check out copies of the book.

In the rare case that there is a change in readings, students will be notified by email well in advance of the week for which those readings are intended.

Session 1: Counterfactual causality	
Learning Objective	(a) Understanding why causality matters in social science and policy; (b) Grasping the difference between associations, interventions, and counterfactuals.
Required Readings	**Impact Evaluation**: Chapters 1-2 (Why evaluate? Preparing for an evaluation) Also, watch any of the following videos (about 1 hour each): – Andrew Gelman: 100 Stories of Causal Inference https://youtu.be/jnI5KI843Lk

	– Interview with Judea Pearl https://youtu.be/hB9xDcumnHY – Interview with Donald Rubin https://youtu.be/mljZc8ly9KY – Interview with Esther Duflo https://youtu.be/WWW9q30MYxU – Judea Pearl: The New Science of Cause and Effect https://youtu.be/ZaPV1OSEpHw – Fireside chat with Susan Athey: https://youtu.be/ypHLWbtqepo
Optional Readings	Freedman, David A. "Statistical Models and Shoe Leather." *Sociological Methodology* 21 (1991): 291–313. Rubin, D. B. (2008). For Objective Causal Inference, Design Trumps Analysis. *The Annals of Applied Statistics*, 2(3), 808–840.

Session 2: The potential outcomes framework and experiments	
Learning Objective	(a) Understanding the potential outcomes framework (POF), and the perils of selection bias for inference; (b) Assumptions behind POF; (c) Average treatment effect; (d) Value of randomization and experiments.
Required Readings	**Impact Evaluation**, Chapters 3-4 (Causal inference and counterfactuals, Randomized assignment) **The Mixtape**: Chapter 5 (Potential outcomes causal model) **What if**: Chapters 1, 2 (A definition of causal effect; Randomized experiments) **Mastering Metrics**: Chapter 1 (Randomized Trials)
Optional Readings	Duflo, E., Glennerster, R., & Kremer, M. (2008). Using Randomization in Development Economics Research: A Toolkit. In T. P. Schultz & J. A. Strauss (Eds.), *Handbook of Development Economics* (Vol. 4, pp. 3895–3962). Amsterdam, NL: Elsevier. Morgan, S. L., & Winship, C. (2015). *Counterfactuals and Causal Inference: Methods and Principles for Social Research* (2nd ed.). New York: Cambridge University Press. Chapter 2.

Session 3: Causal graphs	
Learning Objective	(a) Directed Acyclical Graphs (DAGs); (b) Uses and usefulness; (c) Principles of DAGs; (d) Identification criteria; (e) D-separation; (f) Confounding.
Required Readings	**The Mixtape**: Chapter 4 (Directed acyclical graphs) **What if**: Chapter 6 (Graphical representation of causal effects)
Optional Readings	Elwert, F. (2013). Graphical Causal Models. In S. L. Morgan (Ed.), *Handbook of Causal Analysis for Social Research* (pp. 245–273). Dordrecht: Springer Netherlands. Pearl, J., Glymour, M., & Jewell, N. P. (2016). *Causal Inference in Statistics: A Primer*. Chichester, UK: Wiley. Chapter 1 [starting from 1.4] and Chapter 2.

	Morgan, S. L., & Winship, C. (2015). *Counterfactuals and Causal Inference: Methods and Principles for Social Research* (2nd ed.). New York: Cambridge University Press. Chapter 3.

Session 4: Regression estimators of causal effects	
Learning Objective	(a) OLS mechanics and estimation. (b) Omitted variables. (c) Regression from a causal perspective. (d) Post-treatment bias.
Required Readings	**Mastering Metrics**: Chapter 2 (Regression) **The Mixtape**: Chapter 3 (Properties of regression)
Optional Readings	Gelman, Andrew, and Jennifer Hill. *Data Analysis Using Regression and Multilevel/Hierarchical Models*. Cambridge: Cambridge University Press, 2007. Chapter 9, esp. Section 9.5 onwards. Angrist, Joshua David, and Jörn-Steffen Pischke. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton: Princeton University Press, 2009. Section 3.2.
Application Reading	Egan, Patrick J., and Megan Mullin. "Turning Personal Experience into Political Attitudes: The Effect of Local Weather on Americans' Perceptions about Global Warming." *The Journal of Politics* 74, no. 3 (July 1, 2012): 796–809.

Session 5: Matching	
Learning Objective	(a) Matching compared to regression. (b) Matching methods. (c) Specification.
Required Readings	**Impact Evaluation**: Chapter 8 (Matching) **The Mixtape**: Chapter 6 (Matching and subclassification) **What if**: Chapter 15 (Outcome regression and propensity scores)
Optional Readings	Stuart, Elizabeth A. "Matching Methods for Causal Inference: A Review and a Look Forward." *Statistical Science* 25, no. 1 (February 2010): 1–21. Ho, Daniel E., Kosuke Imai, Gary King, and Elizabeth A. Stuart. "Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference." *Political Analysis* 15, no. 3 (June 20, 2007): 199–236. Morgan, S. L., & Winship, C. (2015). *Counterfactuals and Causal Inference: Methods and Principles for Social Research* (2nd ed.). New York: Cambridge University Press. Chapter 5.
Application Reading	Gilligan, M.J., & Sergenti, E.J. (2008). Do UN Interventions Cause Peace? Using Matching to Improve Causal Inference. *Quarterly Journal of Political Science* 3: 89—122.

Session 6: Instrumental variables	
Learning Objective	(a) IV definition. (b) Exclusion restriction. (c) Two-stage least squares.
Required Readings	**Impact Evaluation**: Chapter 5 (Instrumental variables) **Mastering Metrics**: Chapter 3 (Instrumental variables) **The Mixtape**: Chapter 8 (Instrumental variables) **What if**: Chapter 16 (Instrumental variable estimation)
Optional Readings	Sovey, Allison J., and Donald P. Green. "Instrumental Variables Estimation in Political Science: A Readers' Guide." *American Journal of Political Science* 55, no. 1 (2011): 188–200. Dunning, Thad. *Natural Experiments in the Social Sciences: A Design-Based Approach*. Cambridge: Cambridge University Press, 2012. Chapter 4.
Application Reading	Kern, H.L. and J. Hainmueller. (2009). Opium for the Masses: How Foreign Media Can Stabilize Authoritarian Regimes. *Political Analysis* 17(4): 377-399.

Mid-term Exam Week: 22 – 26.03.2021 – no class

Session 7: Regression discontinuity designs	
Learning Objective	(a) Connection with experimental assignment; (b) the *sharp* RD design; (c) choices in RD designs; (d) the *fuzzy* RD design; (e) links between *fuzzy* RD and IV estimation
Required Readings	**Impact Evaluation**: Chapter 6 (Regression discontinuity design) **Mastering Metrics**: Chapter 4 (Regression discontinuity designs) **The Mixtape**: Chapter 7 (Regression discontinuity)
Optional Readings	Cattaneo, M. D., Idrobo, N., & Titiunik, R. (2019). *A Practical Introduction to Regression Discontinuity Designs: Foundations*. New York: Cambridge University Press. Sekhon, J. S., & Titiunik, R. (2017). On Interpreting the Regression Discontinuity Design as a Local Experiment. In *Regression Discontinuity Designs* (Vol. 38, pp. 1–28). Bingley, UK: Emerald Publishing Limited. Hausman, C., & Rapson, D. S. (2018). Regression Discontinuity in Time: Considerations for Empirical Applications. *Annual Review of Resource Economics*, 10(1), 533–552. Lee, D. S., & Lemieux, T. (2015). Regression discontinuity designs in social sciences. In *The SAGE Handbook of Regression Analysis and Causal Inference* (pp. 301–326). London: SAGE Publications.
Application Reading	Carpenter, C. & Dobkin, C. (2009). The Effect of Alcohol Consumption on Mortality: Regression Discontinuity Evidence from the Minimum Drinking Age. *American Economic Journal: Applied Economics* 1(1): 164—182.

Session 8: Difference-in-differences and synthetic controls	
Learning Objective	(a) DiD. (b) Synthetic control method. (c) Diagnostics.
Required Readings	**Impact Evaluation**: Chapter 7 (Difference-in-differences) **Mastering Metrics**: Chapter 5 (Differences-in-differences) **The Mixtape**: Chapters 10, 11 (Differences-in-differences, Synthetic control)
Optional Readings	Abadie, Alberto, Alexis Diamond, and Jens Hainmueller. "Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program." *Journal of the American Statistical Association* 105, no. 490 (2010): 493–505. Abadie, Alberto, Alexis Diamond, and Jens Hainmueller. "Comparative Politics and the Synthetic Control Method." *American Journal of Political Science* 59, no. 2 (2015): 495–510.
Application Reading	Dube, Oeindrila, Omar García-Ponce, and Kevin Thom. (2016). From Maize to Haze: Agricultural Shocks and the Growth of the Mexican Drug Sector. *Journal of the European Economic Association* 14: 1181–1224.

Session 9: Panel data	
Learning Objective	(a) Basics: interrupted time series models; (b) Features of panel data; (c) Adjustment strategies; (d) Fixed effects properties
Required Readings	**The Mixtape**: Chapter 9 (Panel data) Bell, A., & Jones, K. (2015). Explaining Fixed Effects: Random Effects Modeling of Time-Series Cross-Sectional and Panel Data. *Political Science Research and Methods*, 3(01), 133–153.
Optional Readings	Imai, K., & Kim, I. S. (2019). When Should We Use Unit Fixed Effects Regression Models for Causal Inference with Longitudinal Data? *American Journal of Political Science*, 63(2), 467–490. Morgan, S. L., & Winship, C. (2015). *Counterfactuals and Causal Inference: Methods and Principles for Social Research* (2nd ed.). New York: Cambridge University Press. Chapter 11. Brüderl, J., & Ludwig, V. (2015). Fixed-effects panel regression. In *The SAGE Handbook of Regression Analysis and Causal Inference* (pp. 327–357). London: SAGE Publications. Clark, T. S., & Linzer, D. A. (2015). Should I Use Fixed or Random Effects? *Political Science Research and Methods*, 3(2), 399–408.
Application Reading	O'Grady, T. (2019). How do Economic Circumstances Determine Preferences? Evidence from Long-run Panel Data. *British Journal of Political Science*, 49(4), 1381–1406.

Session 10: Moderation and heterogeneous effects

Learning Objective	(a) Moderation and mediation. (b) Heterogeneous effects. (c) Estimation and interpretation.
Required Readings	Brambor, Thomas, William Roberts Clark, and Matt Golder. "Understanding Interaction Models: Improving Empirical Analyses." *Political Analysis* 14, no. 1 (2006): 63–82. Baron, Reuben M., and David A. Kenny. "The Moderator-Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic, and Statistical Considerations." *Journal of Personality and Social Psychology* 51, no. 6 (1986): 1173–1182.
Optional Readings	Angrist, Joshua David, and Jörn-Steffen Pischke. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton: Princeton University Press, 2009. Section 4.4. Hainmüller, J., Mummolo, J., and Xu, Yiqing. (2019). How Much Should We Trust Estimates from Multiplicative Interaction Models? Simple Tools to Improve Empirical Practice. *Political Analysis* 27(2): 163—192.
Application Reading	Gidengil, Elisabeth, Hanna Wass, and Maria Valaste. "Political Socialization and Voting: The Parent–Child Link in Turnout." *Political Research Quarterly* 69, no. 2 (June 1, 2016): 373–83.

Session 11: Validity and generalizability	
Learning Objective	(a) Construct validity, (b) Statistical conclusion validity, (c) Internal validity, (d) External validity, (e) Generalization of study results
Required Readings	**Impact Evaluation**: Chapter 9 (Addressing methodological challenges) Coppock, A. 2020. 10 things to know about statistical power. https://egap.org/resource/10-things-to-know-about-statistical-power/.
Optional Readings	Hünermund, P. & Louw B. 2020. On the Nuisance of Control Variables in Regression Analysis. https://arxiv.org/abs/2005.10314. Kern, Holger L., Stuart, Elisabeth A., Hill, Jennifer, and Green, Donald P. 2016. Assessing methods for generalizing experimental impact estimates to target populations. *Journal of Research on Educational Effectiveness* 9: 103-127. Lesko, Catherine R., Buchanan, Ashley. L., Westreich, Daniel, Edwards, Jessie K., Hudgens, Michael G., and Cole, Stephen R. 2017. Generalizing study results: a potential outcomes perspective. *Epidemiology* 28: 553-561 Stuart, E. A., & Rhodes, A. (2016). Generalizing Treatment Effect Estimates From Sample to Population: A Case Study in the Difficulties of Finding Sufficient Data. *Evaluation Review*, 41(4), 357–388.

Session 12: Developing, planning, and running evaluations

Learning Objective	(a) Choosing the right method, (b) Managing an impact evaluation, (c) Research ethics, (d) Disseminating results
Required Readings	**Impact Evaluation**: Chapters, 11-14 (Choosing an impact evaluation method, Managing and impact evaluation, The ethics and science of impact evaluation, Disseminating results and achieving policy impact)
Optional Readings	Loukides, M., Mason, H., and Patil, D.J. (2018). *Ethics and Data Science*. O'Reilly.

Final Exam Week: 17 – 21.05.2021 – no class