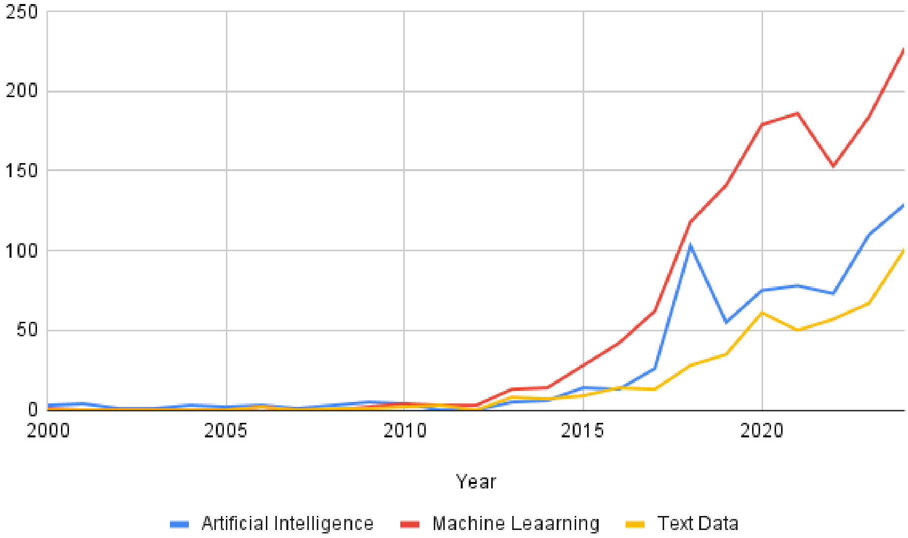
Data Science for Public Policy
From Econometrics to AI

Introduction

ETH Zurich

20/02/2024

Data Science in Economics



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  - We want policies to be correctly designed
  - We want policies to be correctly evaluated
- This is where tools from **data science** and *econometrics* come in handy
- **Causal inference methods** from applied economics and **machine learning techniques** are perfect to evaluate and support better policies

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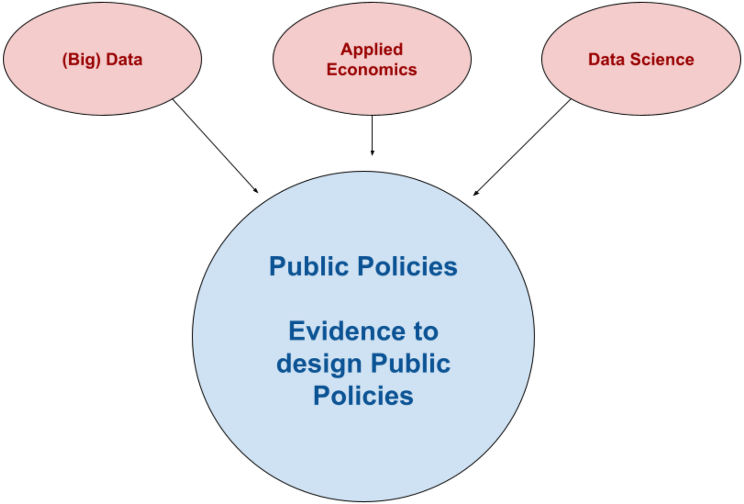

Some Concepts We Will Explore

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- Data Science:
  - ML/AI optimal methods to make predictions
  - Allow the analysis of different data formats, e.g., text, images, audio
  - Perfect for generating risk assessment and tailoring actions

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- Does immigrant legalization reduce crime?

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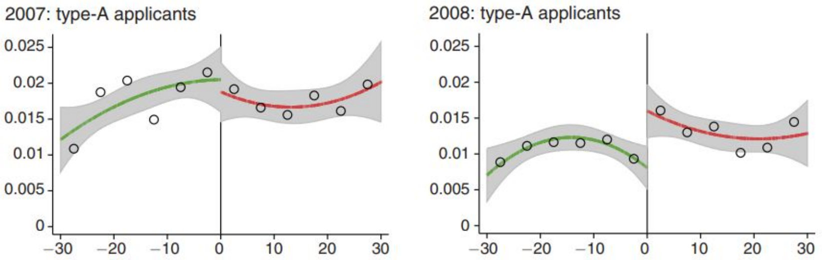

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Altindağ et al. 2022 RESTAT - Government-Sponsored Information Campaign on Infant Mortality

- Does government-sponsored campaigns affect health outcomes?

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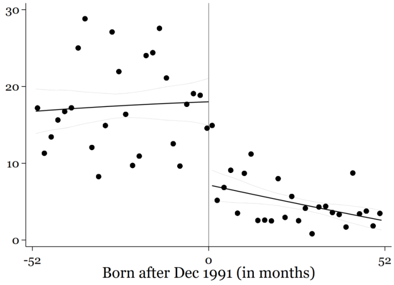

(A) SIDS mortality

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Aiken et al. 2022 NATURE - Machine learning to improve targeting of humanitarian aid

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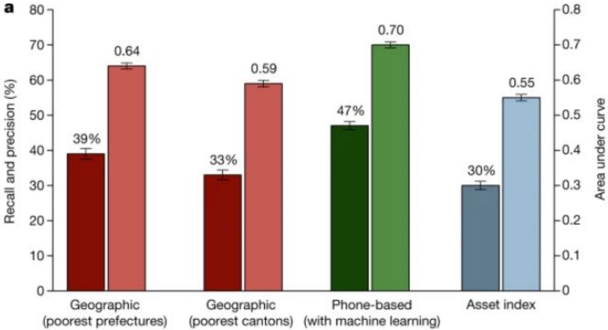
Fig. 1: Comparing Novissi targeting to alternatives.



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Ash et al. 2024 AEJPOL - Machine learning to detect corruption

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Table 4: Performance Metrics for Targeted Auditing Policies

	Status Quo (Lottery)		Targeted Audits		Fair Targeting
	(1a)	(1b)	(2a)	(2b)	(3)
Evaluation Sample	All (Sim)	Audited	All (Sim)	Audited	All (Sim)
Corruption Rate, if Audited	0.486	0.458	0.871	0.883	0.868
$\hookrightarrow$ Ratio over Random Audits			[1.788]	[1.927]	[1.783]
Audit Rate, if Corrupt	0.036	0.036	0.076	0.119	0.074
$\hookrightarrow$ Ratio over Random Audits			[2.714]	[4.246]	[2.644]

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Hansen et al. 2023 QJE - Transparency and Deliberation Within the FOMC

- How does transparency affect monetary policy makers' deliberations?

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Difference-in-Differences Results for Policy Strategy Discussion (FOMC2): Topic Measures

Main regressors	Concentration (1)	Quant (2)	Avg Sim (B) (3)	Avg Sim (D) (4)	Avg Sim (KL) (5)	Pr (No Dissent) (6)
D(Trans) × Fed experience	−0.00077**	−0.00011	−0.00019	−0.00041***	−0.00040	−0.0015**
	[.014]	[.323]	[.222]	[.006]	[.377]	[.025]
Fed experience	−0.21***	−0.0035	−0.057	−0.11***	−0.22**	−0.41**
	[.000]	[.911]	[.140]	[.006]	[.045]	[.031]
Rookie effect	8.9**	5.6	0.4	5.5***	1.1	3.5**

Notes. This table reports the results of estimating (DinD) on FOMC member statements from the monetary policy strategy discussion. Dependent variable definitions are in Table IV. Coefficients are labeled according to significance (***$p < .01$, **$p <. 05$, *$p < .1$) while brackets below coefficients report p-values calculated using Driscoll-Kraay standard errors. The rookie effect reports the estimated coefficient on $D(Trans)_t \times FedExp_{it}$ multiplied by 20 (approximate difference in experience between the two modes in Figure VI) as a percentage of the average value of the dependent variable before November 1993. These effects carry the same star labels as the corresponding estimated coefficient on $D(Trans)_t \times FedExp_{it}$.

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Gorodnichenko et al. 2023 AER - The Voice of Monetary Policy

- Can the tone of voices of Central Bankers affect the market?

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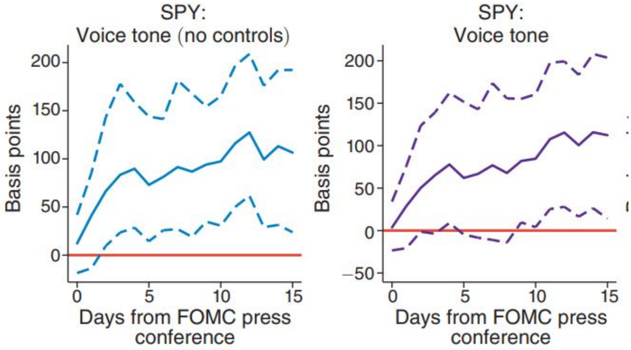

Logistics

- Instructors: Sergio Galletta (sergio.galletta@gess.ethz.ch) & Elliott Ash (ashe@ethz.ch) & Claudia Marangon (claudia.marangon@gess.ethz.ch)
- Lecture Time: Thursdays 12:15-14:00
- Location: In person LFW B 1
- Office hours: By appointment via email
- Most of the important information are in the syllabus and we update the course material on github

Assessment

- Paper presentations (April 17th to May 15th) – **20% of the final grade**
- Final exam (May 22nd) – **30% of the final grade**
- Individual or group project (due on July 22nd) – **50% of the final grade**

Assessment: Paper Presentations

- Group presentations – 2-4 members
- From April 17th to May 15th – 4 presentations per day
  - 15 minutes presentations (only clarifying questions)
  - 5-10 minutes questions and discussion
- Choose a paper from our reading list *OR* propose one in coordination with us
- Sign-up here **by March 13th**

Assessment: Final Project

- Research paper: pick a topic you are interested in!
- Individual or in groups of 2 to 4
- Timeline (more details on syllabus):
  - Choose a topic and sign-up here by **April 9th**
  - Submit 1/2 pages outline by **April 17th**
  - Submit 10 minutes video presentations by **May 30th**
  - Submit final paper with replication package by **July 20th**
- You can reach out to us at any time to discuss your project

Last year projects

- Does the text sentiment of the voting question influence the outcome of Swiss voting? (Paper)
- The causal impact of rainfall on wealth inequality in Vietnam (Paper)
- Who Pays for the Church? Electoral Institutions and Religious Clientelism in Post-War Italy (Paper)
- Modelling Patient Risk and Extraneous Causal Factors in Physician-Decision Making (Paper)
- Renewable Energy Innovation Across the World (APP)