Applied Economics Issues

Introduction

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1. Short presentation and logistics

Instructor

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Course organization

- Duration: 8 sessions (8×3 hours)
- The course will be based on lectures combined with interactive discussions.
- You are expected to actively participate by preparing readings in advance and contributing to classroom debates.
- Some reading materials will be provided in advance.

Objectives of the course

- Train you to think like economists by applying economic reasoning to real-world issues.
- Help you become familiar with reading and summarizing academic articles.

Evaluation

You will be evaluated with a final written exam.

2. Introduction

Our role

What is the role of applied economists today?

Source: Sarah Blesener/The New York Times/Redux/eyevine

Source: Image generated with ChatGPT 5

First example: what drives climate protests?

Source: Sarah Blesener/The New York Times/Redux/eyevine

Based on Fisher et al. (2023, Nature):

Why do people protest?

- To voice political demands
- To express anxiety or concern
- To build collective identity / movement

Which tactics are effective?

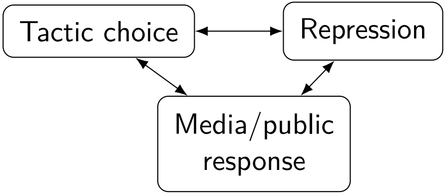
- Wide repertoire of non-violent actions (Sharp, 1973 lists 192)
- Confrontational tactics unpopular, but gain media attention
- Raises cost–benefit questions about visibility vs. legitimacy

Why repression?

- Global wave of criminalization of non-violent protest
- Evidence suggests repression not driven by public opinion
- Open question: what incentives drive governments?

Where do applied economists come in?

- **Collective action problem**
  - Why join if **individual impact is negligible**?
  - Free-rider problem (Olson, 1971)
- **Strategic behavior**
  - protesters and governments: players in a game



- **Externalities and welfare**
  - Climate change: negative externality.
  - Protests: attempt to shift policy to internalize externality.
  - Research question: which tactics minimize social cost while maximizing policy impact?

Economists as problem-solvers

Economists can act as problem-solvers. In the example of climate protests, they can ask (for example):

- How do protests affect the probability of policy change?
- What is the welfare impact of different tactics (costs, benefits, risks)?
- How does repression shift the incentives of citizens and governments?

Hence, economists bring a language of **incentives**, **costs**, and **welfare analysis** to social issues.

Second example: what is going on with AI in hiring? (1/6)

Source: Image generated with ChatGPT 5

1. **According yo you, why would firms adopt AI screening?**
2. **What consequences might there be?**

Second example: what is going on with AI in hiring? (2/6)

Why would firms adopt AI screening?

- Screening is costly: *"The cost of screening applicants, for example reviewing resumes and conducting interviews, is one potentially important friction in the matching process."* (Weinstein 2018, Labour Econ.).
- Scale and speed. *"[algorithmic recommendations] have zero marginal cost, and recommendation quality potentially improves with scale"* (Horton 2017, JLE).
- Perceived objectivity. *"Our review reveals a growing trend in the use of 'blind' screening algorithms to eliminate unconscious human bias by removing demographic markers from application materials, as their disparate influence on decision makers has been shown"* (Cheng and Hackett, 2021).

Second example: what is going on with AI in hiring? (3/6)

Why would firms adopt AI screening?

- A bit more on **perceived objectivity**. Miller (2018, Harv. Bus. Rev.) argues that since humans are bad (not accurate and biased) at making some decisions, this task should be assigned to algorithms: "*the humans who used to make decisions were so remarkably bad that replacing them with algorithms both increased accuracy and reduced institutional biases.*" His claim invokes economic theory: "*This is what economists call a Pareto improvement, where one policy beats out the alternative on every outcome we care about.*"

Second example: what is going on with AI in hiring? (4/6)

Biases everywhere, even for algorithms

- AI algorithms are trained on **historical data** which already contain biases. "*an extensive literature has documented that firms, and the recruiters that they employ, are often inaccurate or biased in their predictions*" (Li et al. 2025, Rev. Econ. Stud.).
- Masking discriminatory variables worsens discrimination for humans: "*before BTB [Ban the Box], white applicants received 7% more callbacks than similar black applicants, but after BTB this gap grew to 43%.*" (Agan and Starr 2017, QJE)
- Dropping a sensitive attribute does not prevent discrimination **if correlated features remain** (proxy issues, as discussed in Dwork et al., 2012).

Second example: what is going on with AI in hiring? (5/6)

The use of AI-guided recruiting decisions leaves us with **multiple concerns**, including:

- Adverse impact across groups. *"because this approach implicitly assumes that past examples extend to future applicants, firms that rely on this approach may favour groups with proven track records, to the detriment of non-traditional applicants."* (Pisanelli 2022, Econ. Lett.).
- Opaque criteria:
  - the models themselves are usually not made public (Raghavan et al. 2020, FACCT),
  - how they operate is usually unintelligible (Ajunwa 2020, Cardozo L. Rev.).
- Feedback loops, as documented by Lum and Isaac, 2016 for crime prediction: *"the model becomes increasingly confident that the locations most likely to experience further criminal activity are exactly the locations they had previously believed to be high in crime: selection bias meets confirmation bias."*

Second example: what is going on with AI in hiring? (6/6)

These concerns leave us with a lot of questions. A very simple one is the following:

Do AI tools improve match quality and equity, or do they just repackage previous biases?

2.1. The role of applied economists

Where do applied economists come in? (1/3)

Measuring causal links

- AI screening tools may alter who is chosen and also the counterfactual pool of who would have succeeded if given the chance.
- There is a need to document **selection and treatment effects**
  - (In)famous example of Amazon's hiring algorithm accused of showing bias against women.[1]
  - Hoffman et al. (2017, QJE) shows, through an experiment, that HR managers who receive **additional signal** thanks to AI-driven job testing "*often overrule test recommendations because they are biased or mistaken*."

[1] https://www.reuters.com/article/us-amazon-com-jobs-automation-insight/amazon-scraps-secret-ai-recruiting-tool-that-showed-bias-against-women-idUSKCN1MK08G/

Where do applied economists come in? (2/3)

Document trade-offs and their costs

- Micro101: firms want to max π. In **Hiring**: pick candidate that max **productivity**.
- But firms also face **legal and ethical constraints**:
  - Laws require equal treatment of individuals (wrt, e.g., gender, race).
  - Algorithms must not reproduce discrimination against **protected groups**.
- **Fairness**: "A prediction is fair if it corresponds to the same standard across groups" (Corbett-Davies et al. 2023, JMLR).
  - Note: there are multiple competing definitions of fairness...
- There may be a **trade-off** between **profit maximization** and **fairness**:
  - **Accuracy vs. fairness are not always aligned** (Kleinberg et al., 2016): Imposing fairness constraints can reduce predictive accuracy while relaxing fairness constraints can increase disparities.

Where do applied economists come in? (3/3)

Applied economists can therefore:

- Quantify the **efficiency gains** of AI screening:
  - Hoffman et al. (2017, QJE): algorithms predicted worker productivity better than humans (measure: tenure), but managers often overrode them.
  - Li et al. (2025, ReStud): hiring algorithms for screening lead to better hiring rates
- Investigate their impacts in terms of equity:
  - Li et al. (2025, ReStud) a common classifier (logit LASSO) increases discrimination wrt race; a contextual bandit decreases it.
  - Agan and Starr (2017, QJE): masking criminal records (Ban the Box) to target fairness turned out to increase discrimination by race.
  - Pisanelli (2022, Econ. Lett.): automated screening instead of human recruiters shrinked by 43 pp the gender gap in candidates' prob. of being interviewed.

Economists as problem-solvers

As in the climate protester example, we can frame economists as problem-solvers here. We might ask:

- What is the **causal impact** of AI screening on **productivity** and **diversity**?
- Which **fairness constraints** (if any) yield the best welfare trade-off?
- Can we design selection rules that are **interpretable**, robust, and efficient?

The role of applied economists

In summary:

- **Identify and frame problems**
  - Define what is at stake (equity, efficiency, welfare).
  - Clarify actors, incentives, and trade-offs.
- **Bring evidence**
  - Collect and organize data.
  - Document patterns and causal effects.
- **Propose and evaluate solutions**
  - Cost–benefit analysis.
  - Distributional impacts.
  - Feasibility and constraints.
- **Inform decision-making**
  - Communicate insights to policymakers, firms, and the public.

To go further: Roth (2002, Econometrica): economist as engineer; Duflo (2017, AER): economist as plumber.

From role to reality

But in reality...

We just mentioned what were the *idealized* roles of applied economists.

In practice, there are **challenges** and **limits**:

- How we ask questions.
- How we communicate results.
- How we deal with complexity, trade-offs, and uncertainty.

Pitfall: wrong questions, poor communication

> The fullest complaint is that too often **researchers ask the wrong questions**, then **communicate the answers badly**. Some of this isn't their fault. Academia rewards novelty rather than usefulness. It also can encourage precision ("did the dog tax affect spending on dog food over its first three months?") rather than breadth ("is taxing pets barking mad?"). And it offers the freedom to think about fixing a single problem with a perfect instrument. Meanwhile, **policy** is more often tasked with fighting **multiple distortions** with limited legal tools.
>
> Keynes (2024, Fin. Times)

Pitfall: jargon and complexity

> For me, the most important quality for economists to have when they are testifying or advising policy-makers is the ability to **express their ideas** on important policy issues **clearly** and **simply**, without jargon. I am most emphatically not asking that economists give overly simple or simplistic advice. In fact, one of the most useful roles an economist can perform is to remind policy-makers that the economy is complex, that we must be keenly aware of the unintended consequences of our actions, and that choices must be made among competing objectives.
>
> Hamilton (1992, JEP)

Pitfall: economists talk trade-offs

> There is a fundamental reason economists can sometimes be unpopular: Their thinking is grounded in **trade-offs** and **constraints**. Economists explain that a **choice must be made between A and B**, while politicians (and the public) often want both. Policymaking would be far easier if we could cut taxes and spend more without raising public debt, contain inflation without raising interest rates, expand global trade without losing jobs. But such trade-offs are unavoidable, even if acknowledging them is often politically inconvenient.
>
> Dynan (2025, IMF Fin. and Dev. Magazine)

> Tell us **what is known** and **with what degree of certainty**, where there is important **disagreement** and why, and the pros and cons of particular courses of action. Then offer your best judgment about the proper course of action.
>
> Hamilton (1992, JEP)

Pitfall: lack of consensus

> We need help in distinguishing between policy advice that represents a broad consensus among economists and advice that has not yet achieved such a consensus or even represents only a fringe minority of economists.
>
> (Hamilton 1992, JEP)

Wrap-up

Let us wrap up. We mentioned the following pitfall:

- Asking wrong questions.
- Communicating poorly.
- Using overly complex jargon.
- Exposing trade-offs might be not well perceived.
- There is a lack of consensus among us on every topic...

Lessons for us

- Applied economists must **balance**:
  - Rigor vs. accessibility.
  - Precision vs. relevance.
  - Simplicity vs. complexity of real-world issues.
- Being transparent about limits and trade-offs is as important as providing answers.
- These are skills you will practice throughout this course.

What can you gain from this course?

- Learn new/complementary knowledge on core economic and societal concepts.
- Strengthen your own (informed) opinion
- Develop your critical thinking skills:
  - the discipline is unsettled on many topics and offers competing perspectives,
  - you need to learn to weight the strengths and weaknesses of contrasting readings.
- You will improve your communication skills (presenting ideas, synthesize arguments).
- This will help you if you want to work in academic research, in data science, in policy, or in industry: you will be better at spotting issues and at framing solutions.

Your opinion

What is one real-world issue you think economists could help address?

Write: a topic (or multiple) and specific questions.

For example:

- Topic: Labour market and AI.
- Questions:
  - Do AI tools improve match quality and equity, or do they just repackage previous biases?
  - Can an AI-based matching algorithm help reducing long-term unemployment?

3. Core lenses of applied economics

From theory to application

- Applied work is rooted in economic **theory**.
- The **theories** provide simplified models of **behaviour**, **incentives**, and **interactions** among agents.
- Applied economists take **insights** from these theories and **test them against evidence**
  - using real-world data,
  - addressing policy questions.

With what tools?

- Applied works rely on multiple tools: different hammers for different nails.
- We will distinguish between two different questions applied economists usually have to answer:
  1. **Does X cause Y?**
     - measuring causal effects.
  2. **How much is X worth?**
     - assigning economic value to things without explicit market prices.
- Econometrics is the common language across methods.

3.1. Econometrics

Econometrics: the root of applied work

- As you already know, econometrics consists in applying statistical models to economic data.
- In applied economics, econometrics can be used for different purposes:
  1. **description**,
  2. **prediction**,
  3. **causality**.

The econometric toolbox

Among the different existing econometric methods, the main are:

- **Regression analysis**: the jackknife of econometrics.
- **Panel data methods**: to exploit variation over two dimensions, usually over time and across individuals.
- **Instrumental variables** (IV): to handle endogeneity with external sources of variation.
- **Difference-in-Differences** (DiD): to compare treated vs. control before/after policy.
- **Regression Discontinuity** (RD): to exploit cutoffs or thresholds.

This list is obviously not exhaustive and will probably evolve with time.

Regression analysis example: Mincer's earnings function

- A nice example of **regression analysis** is that of Mincer (1974, NBER).
- The research question is: how do schooling and on the job training determine wages over working life?
- The paper mostly relies on a 1/1,000 sample from the U.S. Census of Population microdata (1950 and 1960).

Regression analysis example: Mincer's earnings function

Assumptions in Mincer (1974, NBER):

- Theoretically: investment in human capital leads to higher wages.
- Empirically: log wages increase linearly with years of schooling and concavely with work experience.

$$\ln \underbrace{w_i}_{\text{Wage/income}} = \alpha + \rho \overbrace{S_i}^{\text{Years of schooling}} + \beta_1 \overbrace{X_i}^{\text{Potential experience}} + \beta_2 \underbrace{X_i^2}_{\text{Sq. Potential experience}} + \varepsilon_i \quad (1)$$

- The parameters are estimated with OLS:
  - ρ: average return to one extra year of schooling (each additional year of schooling increases wages by about $\rho \times 100\%$),
  - β_1, β_2: returns to experience (experience increases earnings at a decreasing rate bc of concavity assumption).

Panel data methods example

- **Panel data methods** use repeated observations over time to control for unobserved heterogeneity.
- For example, Ashenfelter and Card (1985, REStat) use panel data on participants and nonparticipants in 1976 U.S. training programs implemented by the Congress:
  - The authors want to estimate the effectiveness of the training programs designed to raise the earnings of unemployed and low-income workers.
  - They have longitudinal data for individuals before and after 1976 (Social Security earnings records from 1970 to 1978).
  - They use a fixed effects estimator which can control for unobserved, time-invariant ability when evaluating program impacts.

Panel data methods example

Why do panel data matter here?

- Empirically, earnings of workers who enter training programs often fall in the year or two just before training (because of job loss or lay-offs, for example)
- **If** we only **compare trainees** vs. **non-trainees** at **one point in time** (hence using cross-section data), trainees look like they earn less. Therefore, we might wrongly conclude that training has little effect.
- **If** we do a simple **before/after comparison** on **trainees only**, we would attribute the post-training recovery to the program, but part of it is just reversion to trend after the drop in earnings before entering the training programs.
- By **following the same individuals before and after training**, panel data let us:
  - Control for individual fixed effects (long-run earnings capacity).
  - Observe potential pre-training trends and separate them from true treatment effects.

Panel data methods example

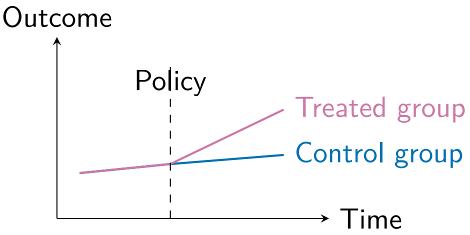
The model from Ashenfelter and Card (1985, REStat) can be simplified to:

$$\overbrace{Y_{it}}^{\text{earnings}} = \underbrace{\omega_i}_{\text{Indiv. FE}} + \overbrace{d_t}^{\text{time effect}} + \beta \underbrace{D_{it}}_{\text{Post-training indicator}} + \varepsilon_{it}$$

- The **individual fixed effect** corresponds to an permanent component, which does not vary with time.
- The **time effect** allows to capture economy-wide shocks.
- The **coefficient β** measures the training effect.

Difference-in-Differences

- **Difference-in-Differences** estimates treatment effect by comparing **before/after differences between groups**.
- The key idea is to use a **control group** to capture general trends, and compare it to a **treated group**.
- We **assume** that in the absence of treatment, trends would have been parallel.



DiD: example

- Card and Krueger (1994, AER) provides an illustration of DiD.
- The papers investigates whether raising the minimum wage reduces employment.
- The authors use survey data of 410 fast-food restaurants in two US States (New Jersey and Pennsylvania), **before and after a policy**:
  - in April 1992, **NJ raised its minimum wage** from $4.25 to $5.05. PA did not.
- NJ is the **treated group**, PA is the **control group**.
- The authors compare changes in employment (before vs. after) across states
- Contrary to competitive labour market theory, employment in NJ did not fall relative to PA.

Difference-in-Differences equation

The equation from Card and Krueger (1994, AER) writes, where i denotes restaurant and t the wave (two waves, before/after reform):

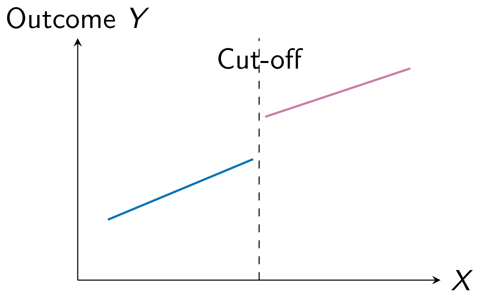
$$\underbrace{Y_{it}}_{\text{employment}} = \alpha + \beta(\underbrace{\text{Post}_t}_{\text{dummy post-policy}} \times \underbrace{\text{NJ}_i}_{\text{dummy treated}}) + \underbrace{\gamma_i}_{\text{restaurant FE}} + \underbrace{\delta_t}_{\text{time FE}} + \varepsilon_{it}$$

- The β **coefficient** measures the estimated effect of NJ's minimum wage increase.

Regression discontinuity

- **Regression Discontinuity** exploits a **cut-off rule** that assigns treatment.
- The **running variable** X decides who is treated:
  - individuals with $X \geq \tau \rightarrow$ **treated** ; individuals with $X < \tau \rightarrow$ **control**
- Near the cut-off τ, individuals are **as good as randomly assigned**.
- Treatment effect is estimated from the **discontinuity in outcomes** at the cut-off.

An example will be shown later on.



3.2. Causal Identification methods

Randomized controlled trials

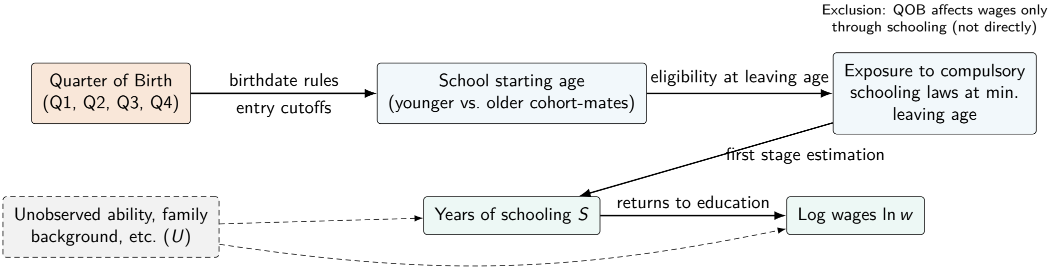
Fields experiments / RCTs

- Randomized Controlled Trial in economics are conducted "in the field", with real-world participants (households, schools, firms, ...).
- Usually designed to evaluate the **causal effect** of an actual **intervention** or **policy**.
- A notable example includes:
  - Miguel and Kremer (2004, Econometrica): school-based deworming in Kenya → positive effects on health and school attendance
- Or: Banerjee et al. (2007, QJE): supplementary inputs given to children from poor families in schools in India → positive (short-run) effects on academic achievement.
- RCTs have **high internal validity** (thanks to randomization):
  - treatment and control groups are, on average, identical in all respects except the intervention,
  - hence the observed effect (if any) is caused by the intervention.
- Limited external validity: context-specific.
- Costly and may pose ethical concerns.

Natural experiments

- Running an RCT may not always be possible (costs, ethics, political reasons, ...).
- In this case, one may turn to **nature experiments**: "nature" (or an institution, but not the researcher) controls the assignment that creates **"as-if random" variation**:
  - this might be the case with a policy change, an exogenous event such as the weather, divides the population, **randomly**, between **treated** and**untreated**.
- Famous example, in the USA: Angrist and Krueger (1991, QJE)
  - Birth month determines school entry age.
  - Compulsory schooling laws bind until 16–17 years old.
  - Together, these rules force some cohorts to stay in school longer.
  - Since **birth month is otherwise random**, it provides **exogenous variation** to estimate **returns to schooling**.
- The **credibility** of natural depends on the "as-if random" assumption (otherwise, the estimates may be biased).

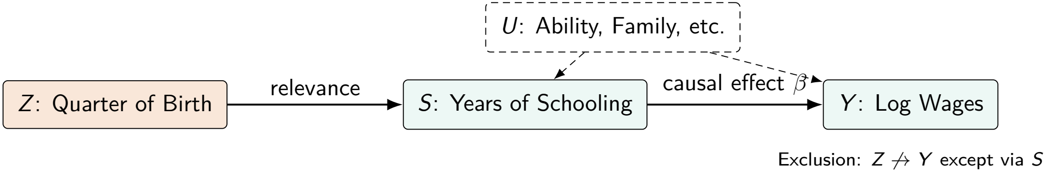
Angrist and Krueger (1991): Quarter of birth as an instrument



Idea: $\Rightarrow$

- Quarter of birth shifts school start/exit timing.
- This induces variation in year of schooling that is unrelated to U (unobserved characteristics).

Angrist and Krueger (1991): IV DAG and 2SLS



The estimation is done using two-stage least squares:

- **First stage**:
  $S_i = \pi_0 + \pi_1 Z_i + \pi' \mathbf{X_i} + u_i$
- **Second stage**:
  $Y_i = \alpha + \beta \widehat{S}_i + \gamma' \mathbf{X_i} + \varepsilon_i$

IV assumptions:

- **Relevance**: $\pi_1 \neq 0$ (the instrument must be correlated with the endogenous regressor).
- **Exclusion**: $Z \perp \varepsilon_i \mid \mathbf{X_i}$ (the instrument must affect the outcome only through the regressor)
- **Independence**: Z as-if random wrt unobservables

Natural experiments: a note on external validity

> The term 'reasonably compelling' is intended to suggest, as one must, that even a reasonably compelling observational study may turn out, in light of subsequent research, to have reached an erroneous conclusion. Sometimes a reasonably compelling observational study prompts investigators to perform a randomized trial, and sometimes the trial does not support the conclusions of the observational study. At other times, several reasonably compelling observational studies point in incompatible directions. When ethical or practical constraints force scientists to rely on observational studies, it is not uncommon to see a decade or more of thrashing about, a decade or more of controversy, conflicting conclusions, and uncertainty. This can be true even when the studies themselves are well designed and executed.
>
> (Rosenbaum, 2017, p. 107)

Natural vs. quasi-natural experiments

When the assignment mechanism (group/treated) is **plausibly exogenous** rather than fully random, one refers to **quasi-natural**.

- Given a good design, one may believe that the assignment is **plausibly exogenous**.
- This requires stronger assumptions and careful econometric methods (e.g., regression discontinuity, diff-in-diff, etc.).

Exercise (1)

In each of the following situations (I'll describe them), answer the following questions:

1. Is the assignment of the treatment **fully random or not**?
2. Is the assignment of the treatment done by a **researcher** or by **nature** (or an institution, independently of what the researcher would like)?
3. Is the experiment and **RCT**, a **natural experiment**, or a **quasi-natural experiment**?

First example: Angrist (1990, AER).

- Research question: Are veterans adequately compensated for their service?
- Treatment: men drafted or not by a lottery in the military (in 1970–1972).

Solution (1)

First example: Angrist (1990, AER).

- Research question: Are veterans adequately compensated for their service?
- Treatment: men drafted or not by a lottery in the military (in 1970–1972).

Answer:

1. The treatment is decided by a random lottery $\rightarrow$ random.
2. The assignment is not made by the researcher for the purpose of his study.
3. The experiment can thus be qualified as a **natural experiment**.

Exercise (2)

In each of the following situations (I'll describe them), answer the following questions:

1. Is the assignment of the treatment **fully random or not**?
2. Is the assignment of the treatment done by a **researcher** or by **nature** (or an institution, independently of what the researcher would like)?
3. Is the experiment and **RCT**, a **natural experiment**, or a **quasi-natural experiment**?

Second example: Pickering et al. (2015, Lancet Glob. Health).

- Research question: Assess the effect of community-led total sanitation on child health in Koulikoro, Mali.
- Treatment: Every household in Rural Mali with at least one child aged younger than 10 years is susceptible to receive community-led total sanitation (randomly selected).

Solution (2)

Second example: Pickering et al. (2015, Lancet Glob. Health).

- Research question: Assess the effect of community-led total sanitation on child health in Koulikoro, Mali.
- Treatment: Every household in Rural Mali with at least one child aged younger than 10 years is susceptible to receive community-led total sanitation (randomly selected).

Answer:

1. The treatment is decided at random.
2. The assignment rule is decided by the team of researchers for the purpose of their study.
3. The experiment can thus be qualified as an **RCT**.

Exercise (3)

In each of the following situations (I'll describe them), answer the following questions:

1. Is the assignment of the treatment **fully random or not**?
2. Is the assignment of the treatment done by a **researcher** or by **nature** (or an institution, independently of what the researcher would like)?
3. Is the experiment and **RCT**, a **natural experiment**, or a **quasi-natural experiment**?

Third example: Angrist and Lavy (1999, QJE).

- Research question: Measuring the effect of class size on test scores.
- Treatment: Public schools in Israel follow the recommendation of twelfth century Rabbinic scholar, the Maimonides, to decide the number of teachers per students. A threshold of 40 pupils in a class is set: if above, two classes (followed by a sharp drop in class size).

Solution (3)

Third example: Angrist and Lavy (1999, QJE).

- Research question: Measuring the effect of class size on test scores.
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Answer:

1. The treatment is not decided at random, but we may believe the assignment mechanism to be plausibly exogenous.
2. The assignment rule is not decided by the two researchers for the purpose of his study. The rule is set by the institution.
3. The experiment can thus be qualified as a **quasi-natural experiment**.

Lab experiments

Lab Experiments

LABoratoire d'EXpérimentation en Economie et Management LABEX-EM, in Rennes (France). Source: CREM.

- Researchers want to **test an economic theory**. They allow to manipulate the environment directly and see causal effects of policy or incentives.
  - e.g., do people cooperate in public goods games?
- Participants are brought into a **controlled setting**, and take part to the experiment:
  - e.g., public goods game to assess if punishment opportunities sustain cooperation? (Fehr and Gächter 2000, AER)
- To align incentives with theoretical payoffs, participants are paid (Smith 1976, AER)
- This tool offers high internal validity.
- But external validity is always questioned: participants are often "WEIRD" (Western, Educated, Industrialized, Rich, and Democratic, Henrich et al. 2010) and thus not representative of broader populations.

3.3. Valuation / preference elicitation methods

Valuation methods

- Applied economists are also interested in **assigning an economics value** to non-market goods and services.
- The central idea is to understand **individual preferences** or **willingness to pay** (for a gain) or to **accept** (for a deterioration).
- Preferences can be either **stated** (respondents are directly asked) or **revealed**.
  - With **stated preferences** , one looks at what people ***say*** they would do in **hypothetical situations**,
  - With **revealed preferences** , one look at what people would ***do*** when they are subject to a choice.
- Choices are then modeled using **structural models**.

Stated preferences

With **stated preferences**, respondents to surveys or experiments are submitted to hypothetical situations. They need to answer, but their response is not incentivized. There are two main approaches.

1. **Contingent Valuation**: survey asks WTP/WTA for a **hypothetical change**.
   - ***What is the max. you are willing tot pay for this change?*** (single valuation)
   - e.g., surveyed hh in China who state how much they would be willing to pay to support gov. programs aiming at reducing air pollution to save lives (Wang and Mullahy, 2006)
2. **Choice Experiments**: respondents choose among scenarios (**hence, hypothetical**) with varying attributes.
   - ***Which option do you prefer?*** (indirect, repeated choices)
   - e.g., in Hanley et al. (1998, ERE), respondents successively selected one of the two proposed options (or the statu quo) described by a price and features for forest management. This allowed to assess their willingness to pay for each feature (forest shape, species mix and feeling pattern and tax levels).

Stated preferences: limits

Stated preferences methods are subjects to some limitations:

- **Cognitive burden**: risk of fatigue, random answers can be provided when the tasks are too difficult.
- **Hypothetical bias**: respondents are asked what they **would** do, their **actual behavior** may differ.
- **Attribute definition problems**: decomposing an option might be too complex and is subject to the researcher's choices
- **Modelling errors**: the choice of a structural model can be wrong, and the assumptions it relies on may be violated.

Revealed preferences

With **revealed preferences**, the inference about how people value goods and services is inferred from observed **market behavior** and **actual choices**.

- The revealed preferences methods use **real market data** (on prices, quantities, on choices made).
- A structural model, like in stated preferences, is used to model individual choices.

We can point out the following main methods:

- **Hedonic pricing** : infers the value of attributes (e.g., clean air, amenities) from their impact on market prices (e.g., housing).
- **Discrete choice models (random utility models)** : derives preferences from observed choices among alternatives, linking choice probabilities to utility.

Revealed preferences: hedonic pricing

- **Hedonic pricing methods** allow us to value **non-market attributes** by analyzing how they affect observed market prices.
- Goods are treated as bundles of **characteristics**:
  - e.g., for houses: size, location, quietness of the neighbourhood, amenities, …
- For example, see Rosen (1974, JPE) for theoretical foundations, and Chay and Greenstone (2005, JPE) or Bajari et al. (2012, AER) for empirical studies.

$$\ln(\overbrace{P_i}^{\text{price}}) = \alpha + \sum_{k=1}^{K} \beta_k \underbrace{Z_{ik}}_{\text{struct. charact.}} + \sum_{m=1}^{M} \gamma_m \overbrace{N_{im}}^{\text{neighb. charact.}} + \sum_{l=1}^{L} \delta_l \underbrace{E_{il}}_{\text{envir. attrib.}} + \varepsilon_i$$

- The **regression coefficients** are referred to as implicit (or hedonic) prices: the effects on the market price of a variation in a particular attribute, *cet. par.*

Revealed preferences: discrete choice models

- With **discrete choice models** and market data, the choices made by agents among discrete alternatives are modelled using probabilistic models.
- It is assumed that a probability can be associated with each alternative. This probability is modelled as a function of the attributes of the alternative.
- Seminal paper: McFadden (1974, JPE) (choice of transport mode to assess urban travel demand, using survey data):
  - The utility of choosing alternative $j \in \mathcal{J}$ of individual n writes $U_{nj} = \mathbf{X}_{nj}\beta + \varepsilon_{nj}$,
  - If the ε_{nj} are i.i.d. with a Gumbel distribution, the prob. that indiv. n chooses option i is:

$$P_{ni} = \frac{\exp(\mathbf{X}_{ni}\beta)}{\sum_{j=1}^{J} \exp(\mathbf{X}_{nj}\beta)}$$

  - This is the **conditional logit model**.

Revealed preferences: limits

Revealed preferences methods are subject to some limits. Here are some:

- they only captures preferences for goods **with observable market behavior**
  - e.g., we can estimate WTP for air quality if it affects house prices (Chay and Greenstone 2005, JPE)
  - but not for non-market goods with no market signal, such as biodiversity conservation or cultural heritage.
- they cannot value **hypothetical or novel goods** (e.g., new environmental policies, future risks).
  - e.g., no way to infer WTP for a new carbon tax or for future climate risks that people have not yet faced.
- Observed behavior may **reflect constraints**, **not pure preferences**.
  - e.g., travel cost method assumes visits reflect demand, but income constraints may prevent poorer households from visiting parks,

Experimental economics: lab/field experiments

- **Lab an field experiments** can also be used to measure preferences:
  - **risk aversion** (e.g., lottery choices à la Holt and Laury (2002, AER)),
  - **time discounting** (e.g., trade-off between an amount today or another amount in t days (Tanaka et al. 2010, AER));
  - **social preferences** (e.g., effect of reputation on a public goods experiment to tackle the tragedy of the commons (Milinski et al. 2002, Nature)).
- Again, lab experiments offer **internal validity** but may be questioned regargind their external validity.
- We mentioned earlier the “WEIRD” critique. For risk aversion, see the large study of L’Haridon and Vieider (2019, Quant. Econ.).

3.4. Wrap-up

Wrap-up

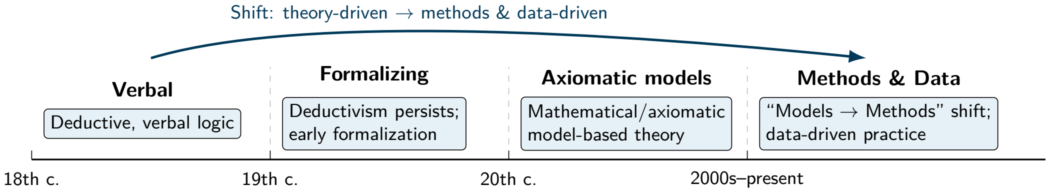
In the applied economist's toolbox, we have seen:

- **Econometrics** : tool used for estimation.
- **Causal identification** (*what happens if... ?*)
  - **Experiments** : field/RCTs (for policy evaluation), lab (for theory testing),
  - **Natural, Quasi-natural experiments** : exploiting "as-if random" variation.
- **Valuation/preferences elicitation** (*how much is it worth?*)
  - **Revealed preferences** (on real or simulated markets),
  - **Stated preferences** (on hypothetical markets),
  - Both approached used to assign economic value to non-market goods.

3.5. A paradigm shift

A shift from theory-driven to data-driven discipline

From Bakeev (2023), we understand that our discipline is not fixed, it it evolving:



- Since the 1970s, economics has transitioned toward empirical work (Panhans and Singleton 2017, Hist. Political Econ.)

From models to methods

- In a provocative article, Leamer (1983, AER) stated that econometricians projects were subject to "*whimsical assumptions*" and subjective judgments. Quote
  - "*Hardly anyone takes data analysis seriously. Or perhaps more accurately, hardly anyone takes anyone else's data analysis seriously.*"
  - "*If it turns out that almost all inferences from economic data are fragile, I suppose we shall have to revert to our old methods lest we lose our customers in government, business, and on the boardwalk at Atlantic City.*"
- As quoted in Panhans and Singleton (2017), going back to Leamer's provocative views, Angrist and Pischke (2010, JEP) wrote, referring to empirical works in the 2000s: "*better research design is taking the con out of econometrics.*"
  - credibility revolution (Garg and Fetzer, 2025), increase of careful designs.

Causal claims in economics: credibility revolution

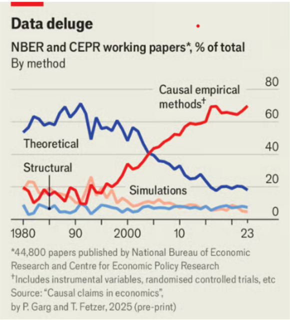


CHART: THE ECONOMIST

But even if economics is not the worst offender, it is no stranger to social science's replication crisis. Its biggest recent trend has been empirical research, with a focus on credible causal designs (see chart). Statistically significant results are prized, incentivising cherry-picking and selective presentation of results. Prashant Garg of Imperial College London and Thiemo Fetzer of the University of Warwick find that the share of papers reporting "null results" fell from 15% in 1980 to 9% in 2023. Use of private data doubled.

Causal claims, from The Economist, covering Garg and Fetzer (2025) who have analyzed over 44,000 working papers from the National Bureau of Economic Research (NBER) and the Centre for Economic Policy Research (CEPR).

4. Positive vs. normative economics

Positive vs. normative economics

Let us go back to our initial question:

What is the role of applied economists today?

- To answer this question, we've seen a brief overview of the discipline.
- Let us end this overview with an answer to the question that addresses what we should and should **not** do, by distinguishing between **positive** and **normative** economics.

Positive economics

- **Positive economics** describes **what is**, not what should be.
- It is about **testing facts**, **statements**, using data.
- For example, we might be interested in testing the following statement:
  - Does a cigarette tax increase affects smoking consumption?
    - Callison and Kaestner (2013): a \$1 increase in cigarette taxes $\rightarrow$ 4% decrease in prob. of being a daily smoker $\rightarrow$ -0.026 price elasticity
    - Kalousova et al. (2020): a \$1 increase in cigarette price was $\rightarrow$ 0.23 decrease of cigarettes smoked daily $\rightarrow$ conditional demande elasticity of -0.05.

Normative Economics

- **Normative economics** prescribes **what ought to be**.
- It is about policy prescriptions and involves judgments/values about fairness, equity, welfare: what should citizens/policymakers do?
- While we can inform on these judgments/values, it is not in our position to decide them (that is up to citizens and policymakers).
- The statements are **not purely testable**.
- For example, we might say:
  - *Smoking creates health costs borne by society (public health system). A tax is justified.* (using an efficiency and an externality criteria).
  - Smoking harms individuals' health even if they choose it. A tax may be justified to protect individuals from their own choices. (using an equity/paternalism criterium).

Why does this distinction matter?

- Distinguishing between **positive** and **normative** economics prevents mixing **facts with opinions**.
- As applied economists, we should provide **credible positive evidence**.
- Weighting **normative trade-offs** is a job left to policymakers.
- Our job is to frame questions, choose and present assumptions, highlight trade-offs.

Your opinion

In the topics/questions you mentioned earlier, do you know if some have sparked debates? What are some differing views?

- Do you know different theories?
- How do economists try to answer the questions, empirically speaking?
- How can it help regarding policy perspectives?

5. Appendix

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Quote from Leamer (1983)

> The applied econometrician is like a farmer who notices that the yield is somewhat higher under trees where birds roost, and he uses this as evidence that bird droppings increase yields. However, when he presents this finding at the annual meeting of the American Ecological Association, another farmer in the audience objects that he used the same data but came up with the conclusion that moderate amounts of shade increase yields. A bright chap in the back of the room then observes that these two hypotheses are indistinguishable, given the available data. He mentions the phrase 'identification problem,' which, though no one knows quite what he means, is said with such authority that it is totally convincing.
>
> Leamer (1983, AER)

Go back