

Social Stratification Research in the Age of Big Data Challenges and Opportunities Ahead

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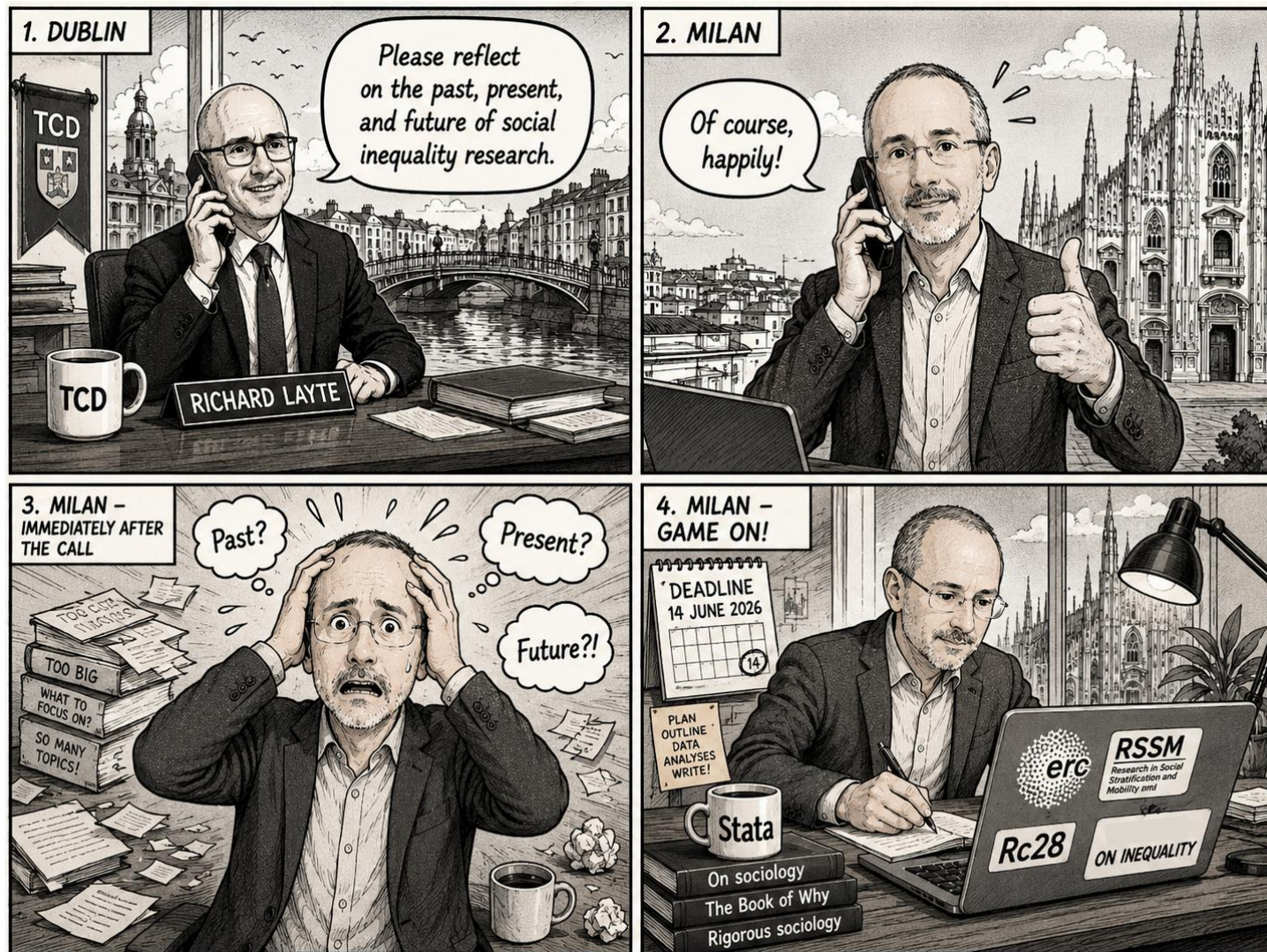
ECSR Conference, Dublin, 15-17 June 2026

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A substantially expanded version of the ideas discussed in the keynote will be published in an editorial article in *Research in Social Stratification and Mobility* in 2026, as part of the journal's 45th anniversary.

Background



Outline of the talk

A roadmap for today's journey



What Have We Learned?

The Expanding Landscape



What Has Changed?

The Data and Methods Revolution



What Are the Risks?

Expansion and Fragmentation



Where Should We Go?

Building a Cumulative Research Programme

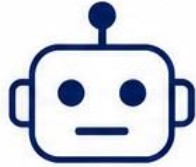


Why Does It Matter?

Understanding and Reducing Inequalities

What I will **NOT** discuss today

Important topics beyond the scope of this talk



Artificial
Intelligence



Data
Privacy



Ethics

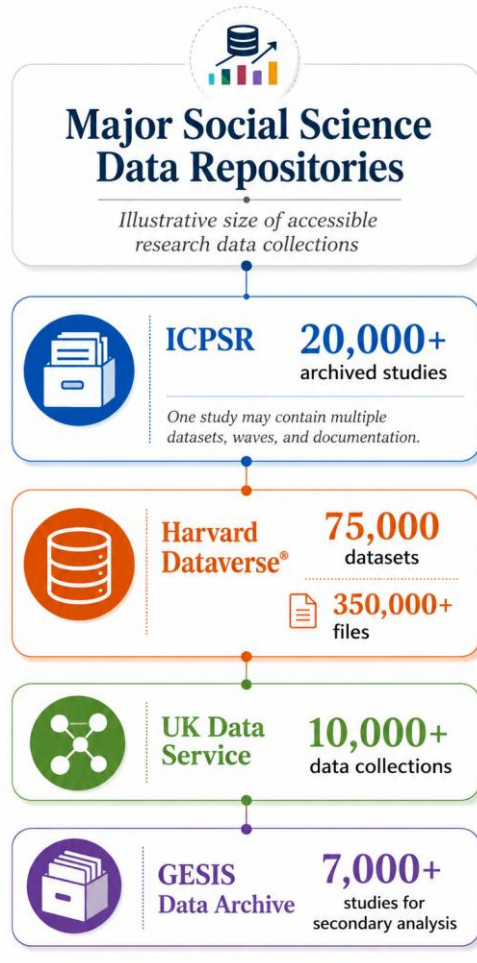


Institutional
Development



Relations with
Policy Makers

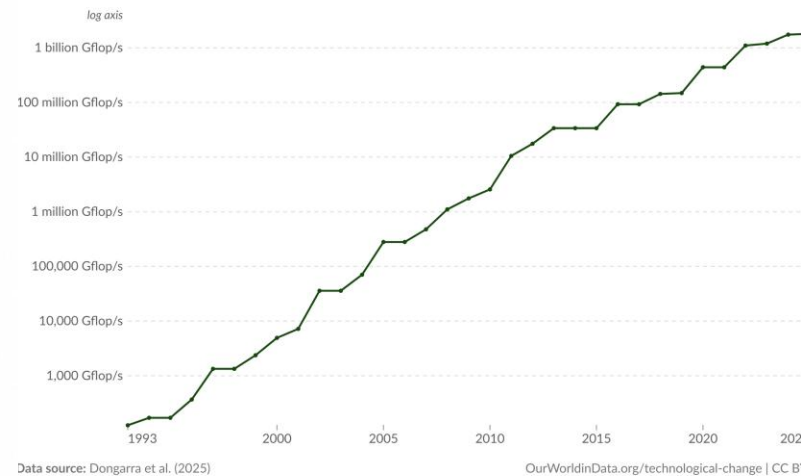
New empirical possibilities: data, software, methods, and computing power



Sources: repository websites. Figures are reported by repositories and are not directly comparable (studies, datasets, files, and data collections differ).

Computational capacity of the fastest supercomputers

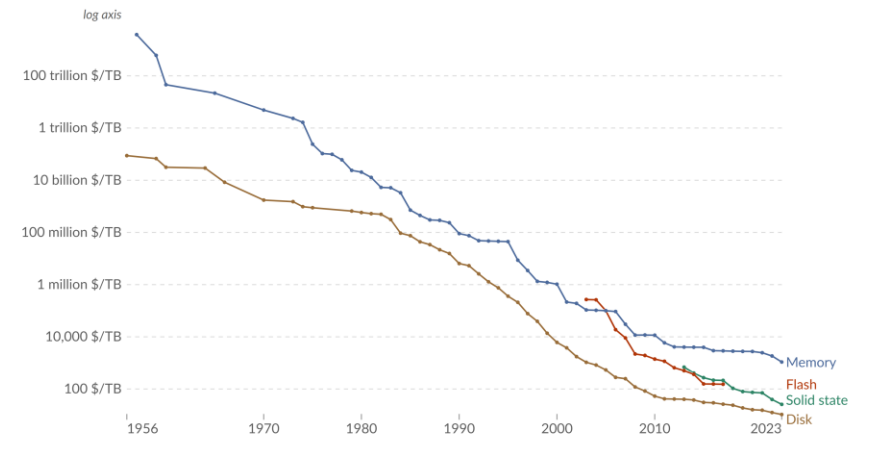
The number of floating-point operations¹ carried out per second by the fastest supercomputer in any given year. This is expressed in gigaflops, equivalent to 10⁹ floating-point operations per second.



1. Floating-point operation A floating-point operation (FLOP) is a type of computer operation. One FLOP represents a single arithmetic operation involving floating-point numbers, such as addition, subtraction, multiplication, or division.

Historical price of computer memory and storage

This data is expressed in US dollars per terabyte (TB), adjusted for inflation. "Memory" refers to random access memory (RAM), "disk" to magnetic storage, "flash" to special memory used for rapid data access and rewriting, and "solid state" to solid-state drives (SSDs).



Note: For each year, the time series shows the cheapest historical price recorded until that year. This data is expressed in constant 2020 US\$.

Software ecosystems: base R includes about **30 packages**; CRAN had **~22,397 active packages** by mid-2025.

Big data and big models

I Just Ran Four Million Regressions

Xavier X. Sala-i-Martin

WORKING PAPER 6252

DOI 10.3386/w6252

ISSUE DATE November 1997

In this paper I try to move away from the Extreme Bounds method of identifying" Instead of analyzing the" extreme bounds of the estimates of the coefficient of a particular variable distribution. My claim in this paper is that, if we do this, the picture emerging from the" empirical growth literature is not the pessimistic Robust" that we get with the" extreme bound analysis. Instead, we find that a substantial number of variables can be found" to be strongly related to growth.

Sociological Methodology



Impact Factor: 2.5 / 5-Year Impact Factor: 4.5

Available access | Research article | First published online July 13, 2018 | [Request permissions](#)

We Ran 9 Billion Regressions: Eliminating False Positives through Computational Model Robustness

[John Muñoz](#) and [Cristobal Young](#) [View all authors and affiliations](#)

[Volume 48, Issue 1](#) | <https://doi.org/10.1177/0081175018777988>

Contents | PDF/EPUB | Cite | Share options | Information, rights and permissions | Met

Abstract



The Journal of Economic History

Where Is the Middle Class? Evidence from 60 Million English Death and Probate Records, 1892–1992

Published online by Cambridge University Press: 16 April 2021

[Neil Cummins](#)

Show author

Article

Figures

Supplementary materials

Metrics



FREE

Workers and the Green-Energy Transition: Evidence from 300 Million Job Transitions

E. Mark Curtis, Layla O'Kane, and R. Jisung Park

PDF

PDF PLUS

Abstract

Full Text



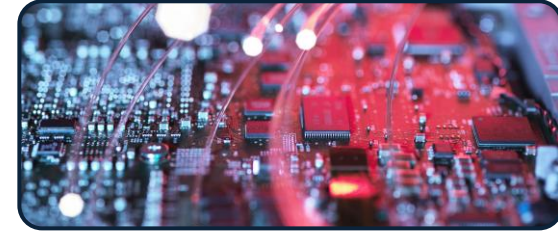
Key question



More
data



More
methods



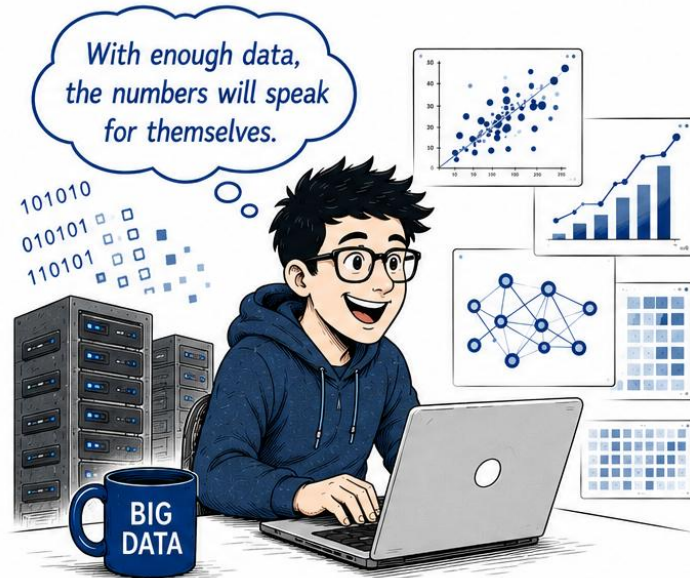
More
computational
power

...better sociology?

Two contrasting positions

THE COMPUTATIONAL ENTHUSIAST

DATA MINING. ALGORITHMS. PREDICTION.



FOCUS

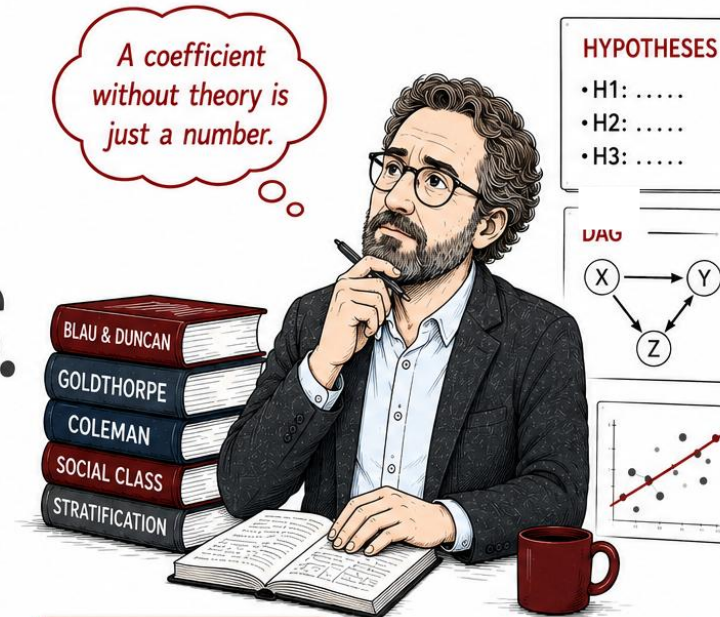
- prediction
- pattern detection
- scalability
- algorithmic performance
- discovery

RISK

- weak theoretical grounding
- unclear constructs
- black-box explanations

THE TRADITIONAL STRATIFICATION RESEARCHER

THEORY. HYPOTHESES. CAUSAL UNDERSTANDING.



FOCUS

- mechanisms
- theory
- causal interpretation
- social meaning
- cumulative knowledge

RISK

- overly restrictive models
- neglect of complexity
- insufficient exploration of heterogeneity

Big data are not enough. Better scientific program



Big data and computational methods are **major opportunity for stratification research**. They might allow to answer...

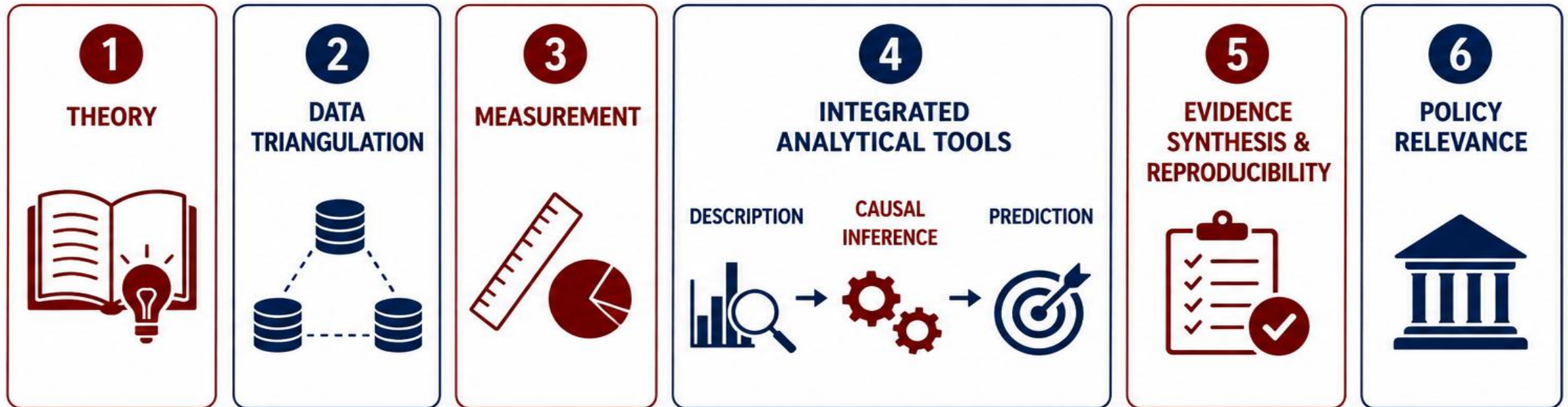
1. Old questions in more refined ways
2. New questions about old problems
3. New questions about emerging topics



But they will strengthen the field only if they are embedded in a **clearer scientific programme**

Developing a rigorous and cumulative social stratification field

Six Pillars for an Integrated Research Programme

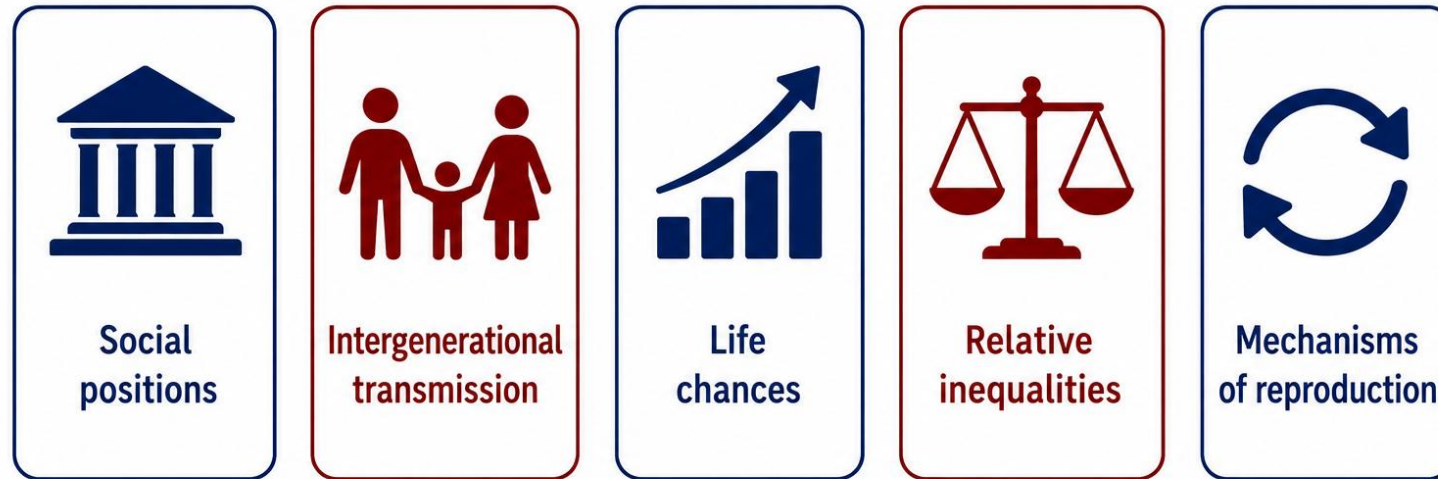


Part I - What Have We Learned?

The Expanding Landscape of Social Stratification Research

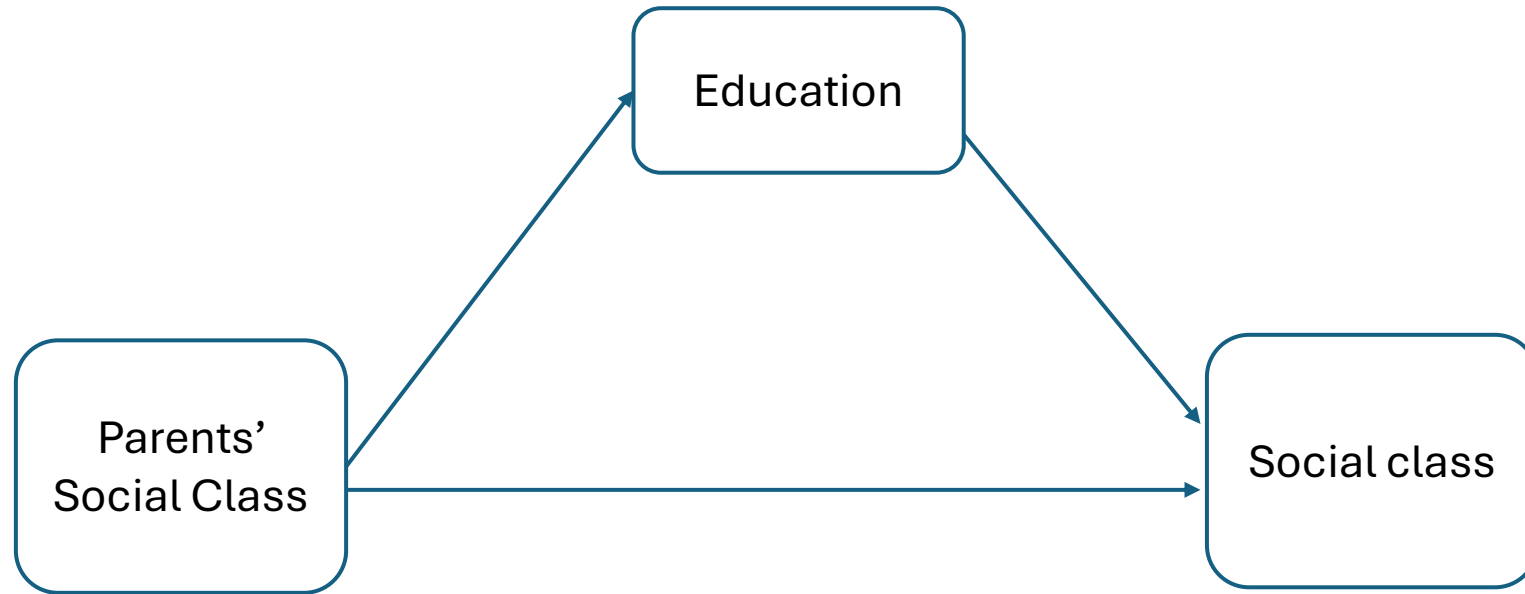
Social stratification research: a definition

Social stratification research studies how **advantages and disadvantages** are **structured, reproduced, and transmitted** across individuals, groups, and generations through systems of **unequal life chances**



(Grusky & Ann 1992; Breen & Jonsson 2005)

The traditional focus of social stratification: the OED triangle



(Blau & Duncan 1968; Erikson & Goldthorpe 1992; Breen 2020)

What have we learned?

SELECTED EMPIRICAL REGULARITIES IN SOCIAL STRATIFICATION RESEARCH



1. SOCIAL MOBILITY AND OCCUPATIONS

- Occupational hierarchies are remarkably stable across countries and over time.
- Social mobility follows common patterns, although its strength varies across contexts and periods.

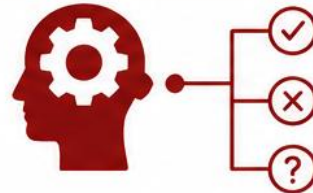
Treiman 1977; Ganzeboom & Treiman 1996; Hauser & Warren 1997; Featherman, Jones & Hauser 1975; Erikson & Goldthorpe 1992; Xie 1992.



2. EDUCATION AND SOCIAL REPRODUCTION

- Education remains the main channel of both upward mobility and intergenerational reproduction.
- Educational expansion reduced inequalities mainly among post-war cohorts; subsequent equalization has been limited.

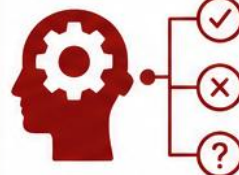
Blau & Duncan 1967; Featherman & Hauser 1978; Treiman & Ganzeboom 1990; Breen et al. 2009; Breen & Müller 2020; Barone & Ruggera 2018; Bukodi & Goldthorpe 2025.



3. PERSISTENT INEQUALITIES BEYOND EDUCATION

- Social origin continues to affect occupational rewards even net of education.
- Gender stratification remains substantial, although historically dynamic and domain-specific.

Torche 2011; Bernardi & Ballarino 2016; Charles & Grusky 1995; Blossfeld & Hakim 1996.



4. MECHANISMS BEHIND EDUCATIONAL INEQUALITIES

- Educational inequalities reflect both academic performance and decision-making processes, with varying importance across countries.
- Rational action remains influential, but recent work suggests a more complex process involving bounded rationality and dual-system mechanisms.

Jackson 2013; Jackson & Jonsson 2013; Breen & Goldthorpe 1997; Breen, van de Werfhorst & Jaeger 2014; Barone 2025.

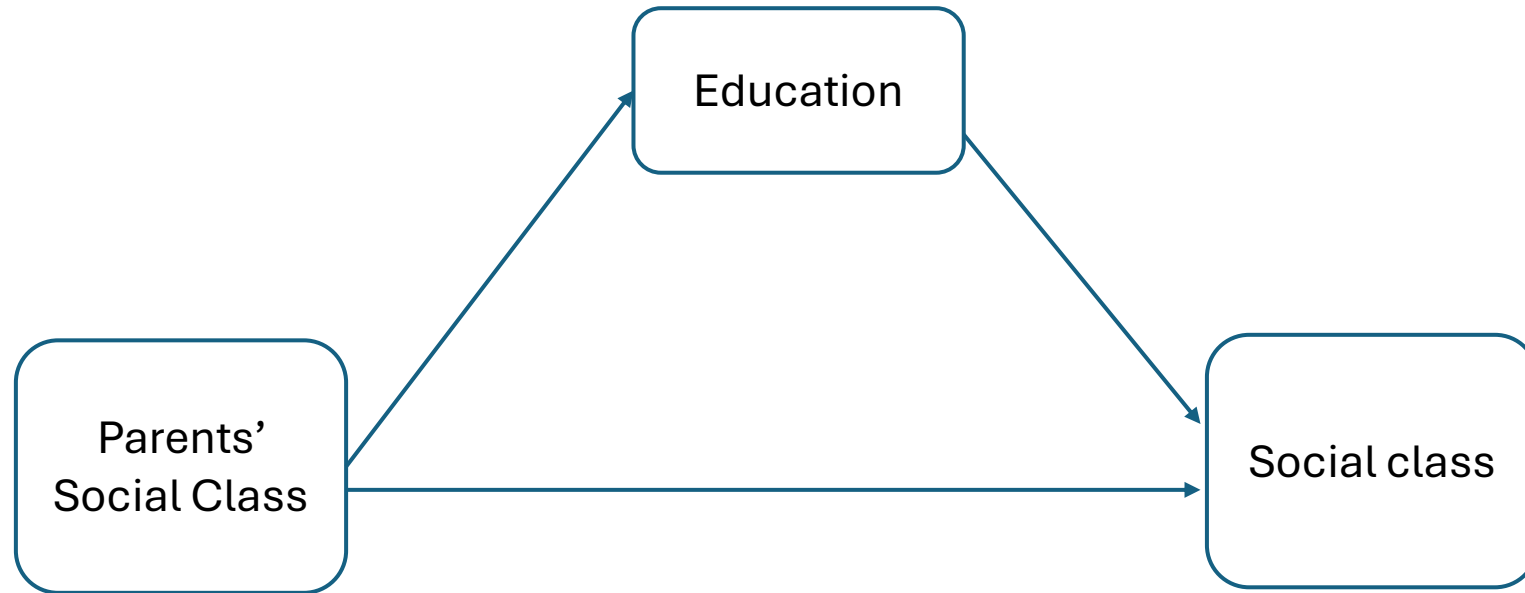


5. EDUCATIONAL INSTITUTIONS MATTER

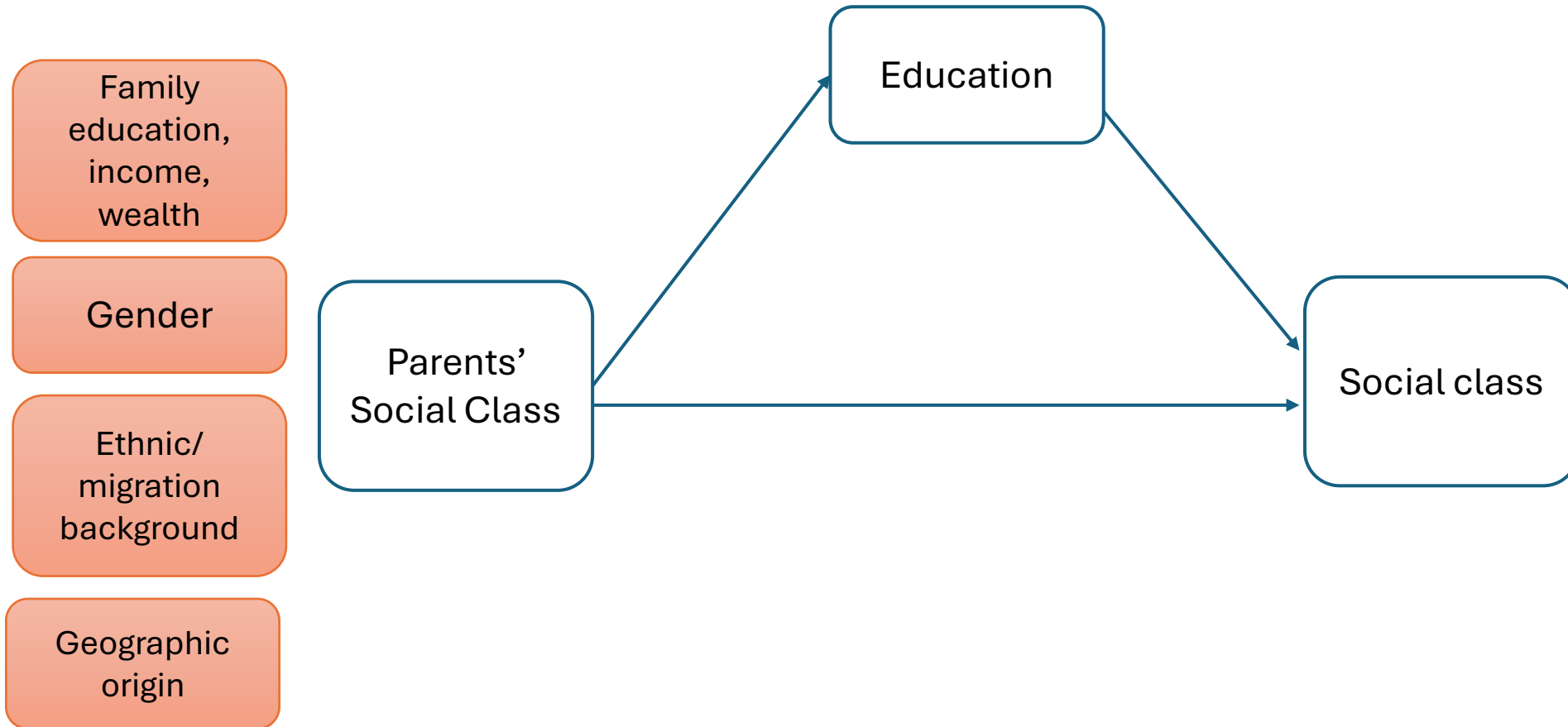
- Tracking and horizontal differentiation shape opportunities at multiple educational stages.
- Institutional arrangements influence the magnitude and persistence of inequalities.

van de Werfhorst & Mijs 2010; Shavit et al. 2007; Triventi 2013; Terrin & Triventi 2023.

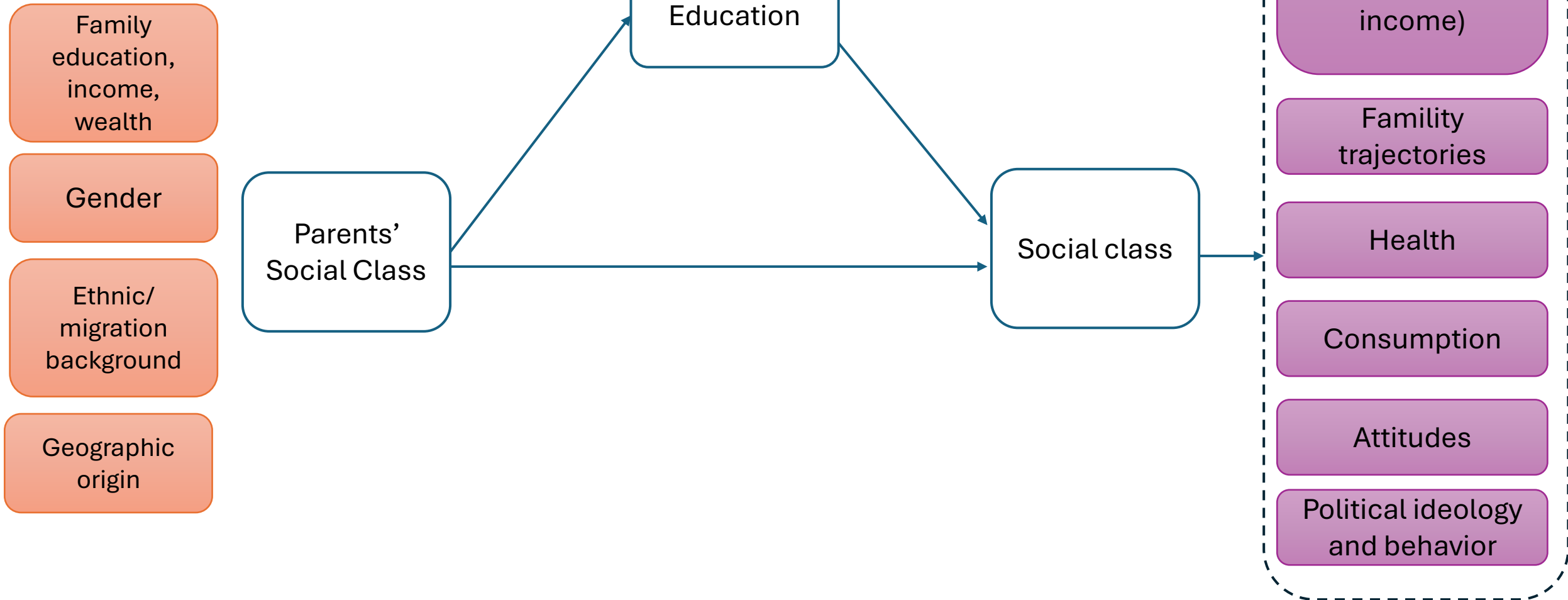
The traditional focus of social stratification: the OED triangle



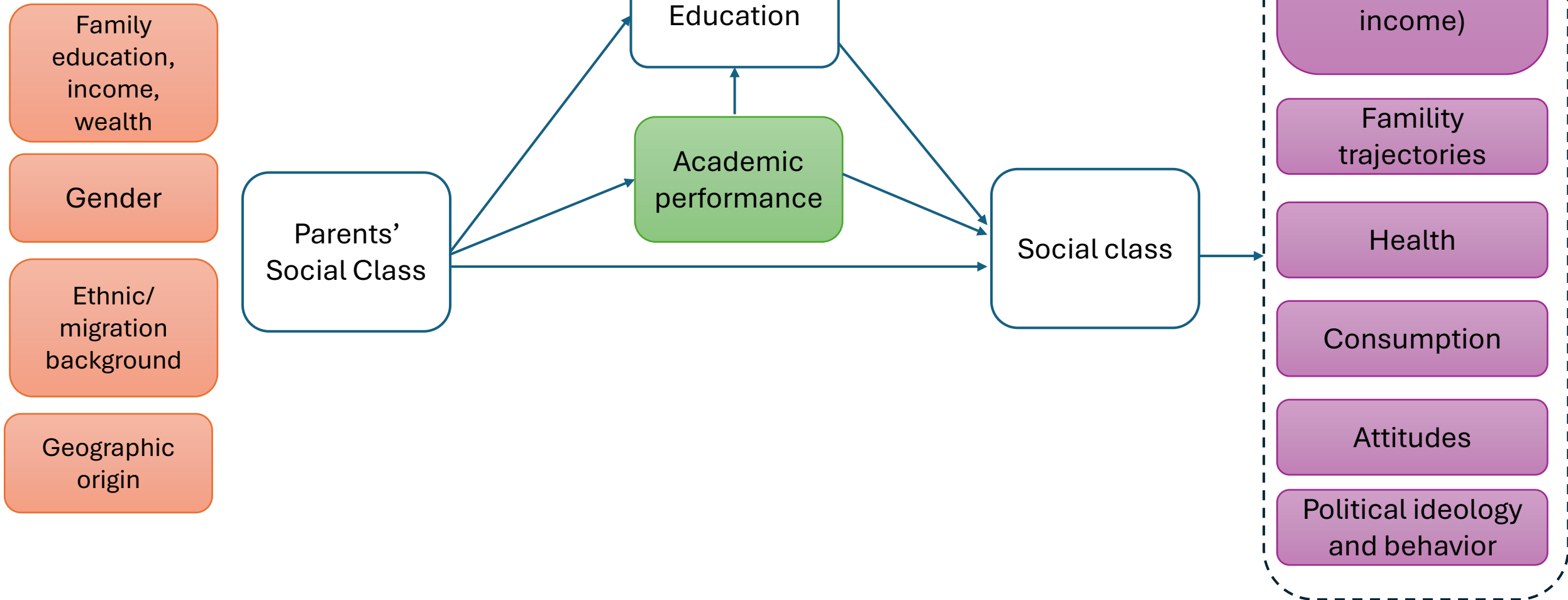
Expansion of the social stratification field



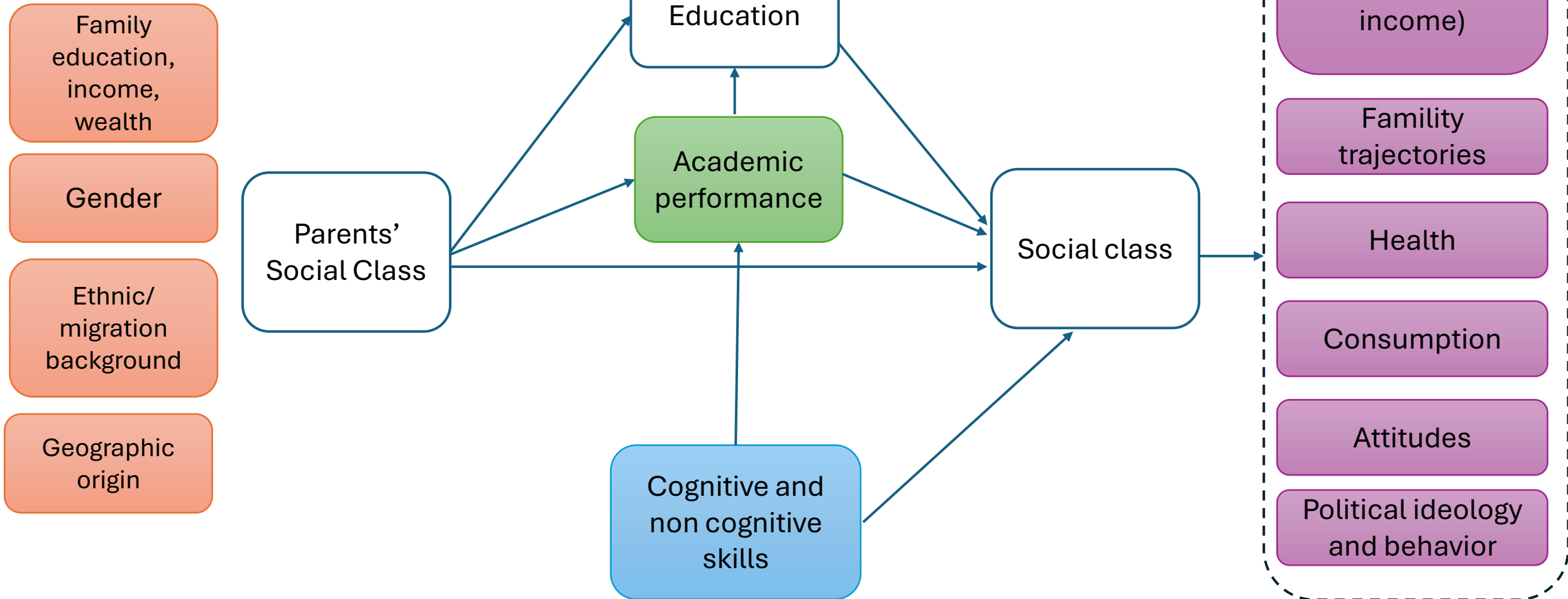
Expansion of the social stratification field



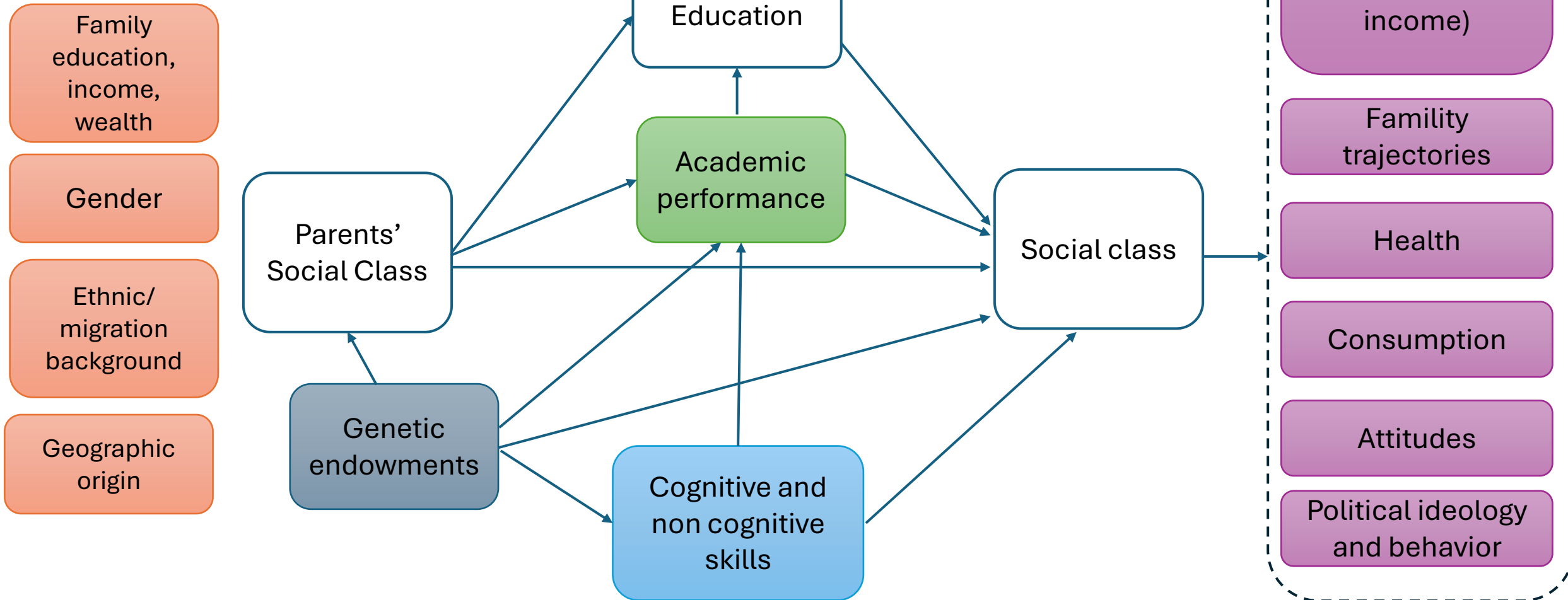
Expansion of the social stratification field



Expansion of the social stratification field



Expansion of the social stratification field



ECSR 2026 Dublin Conference



Part II - What Has Changed?

New possibilities and new challenges

1.1 Expanded data and approaches to study inequalities

Heterogeneous Data Infrastructures for Inequality Research

Diverse data types provide richer insights into the causes and consequences of social inequality.

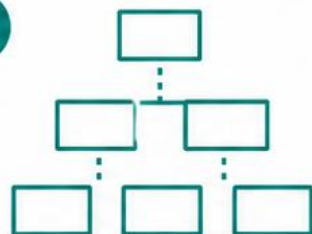
1



Multi-actor data

linked information on students, parents, teachers, partners, peers, and institutions

2



Multilevel data

individuals within classes, schools, neighborhoods, regions, and countries

3



Longitudinal data

repeated measures over time, trajectories, life-course records

4



Administrative data

existing records from public and institutional sources, such as education, tax, health, and employment systems

(Hacker & Petkova 2017; Favaretto et al. 2020)

Heterogeneous Data Infrastructures for Inequality Research

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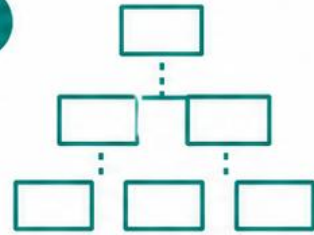
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Multi-actor data

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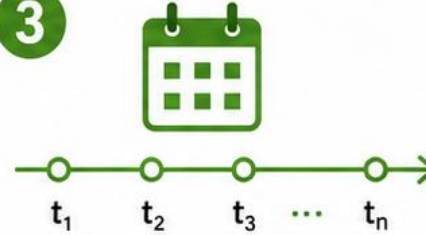
2



Multilevel data

individuals within classes, schools, neighborhoods, regions, and countries

3



Longitudinal data

repeated measures over time, trajectories, life-course records

4



Administrative data

existing records from public and institutional sources, such as education, tax, health, and employment systems

5



Text data

open-ended survey questions, organization reports, email texts, student essays, schools' self-evaluations, online job posts

6



Social media data

posts, interactions, networks, sentiments, digital traces

7



Mobile phone data

mobility patterns, communication behavior, location traces, usage metadata

8

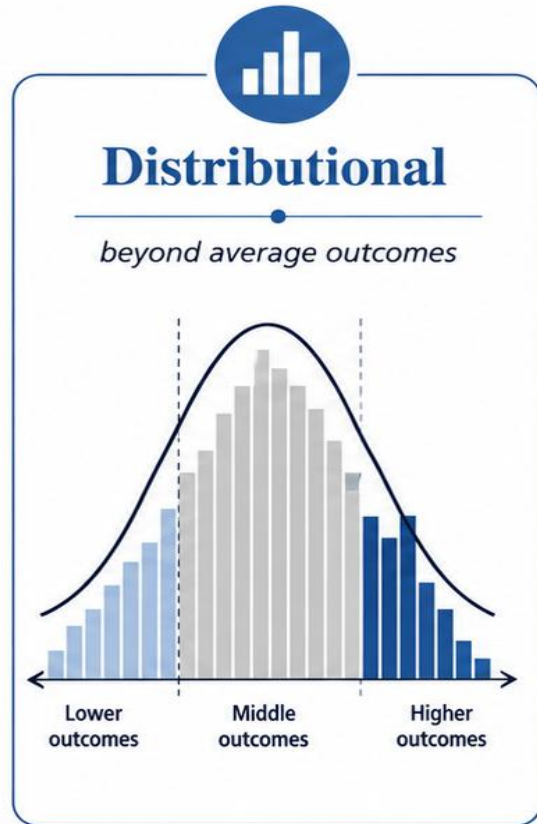


Satellite data

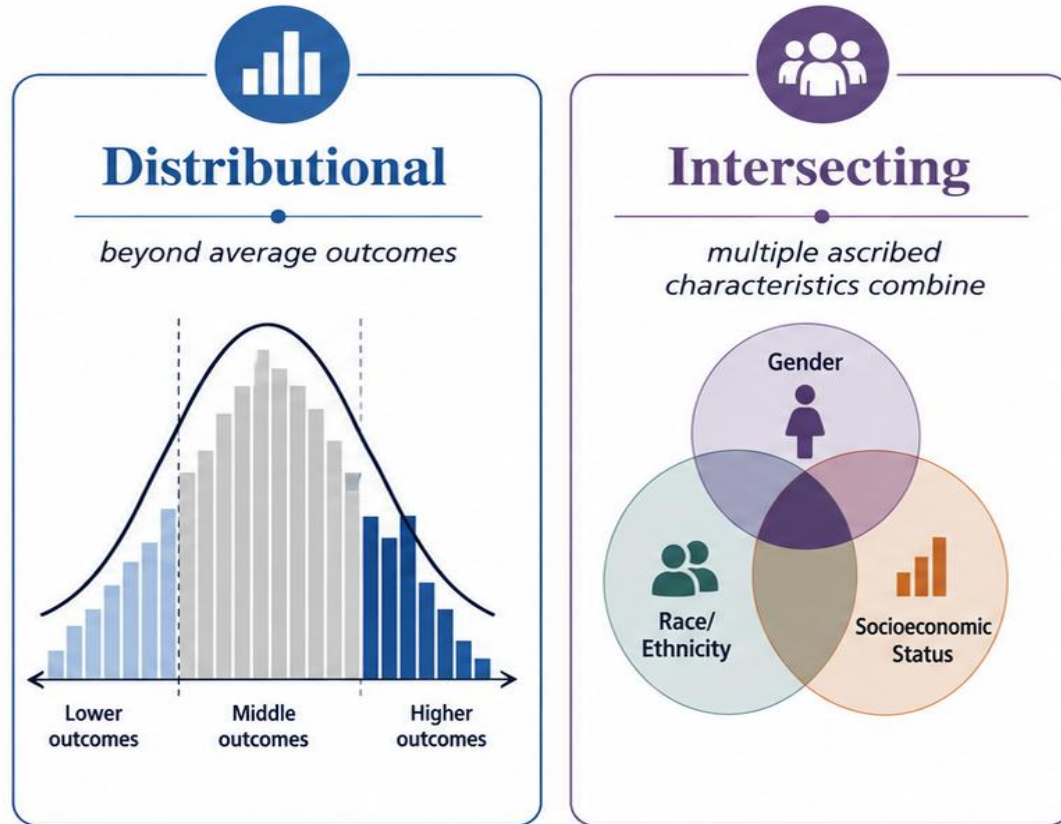
remote sensing for land use, environmental conditions, night lights, spatial exposure

(Hacker & Petkova 2017; Favaretto et al. 2020)

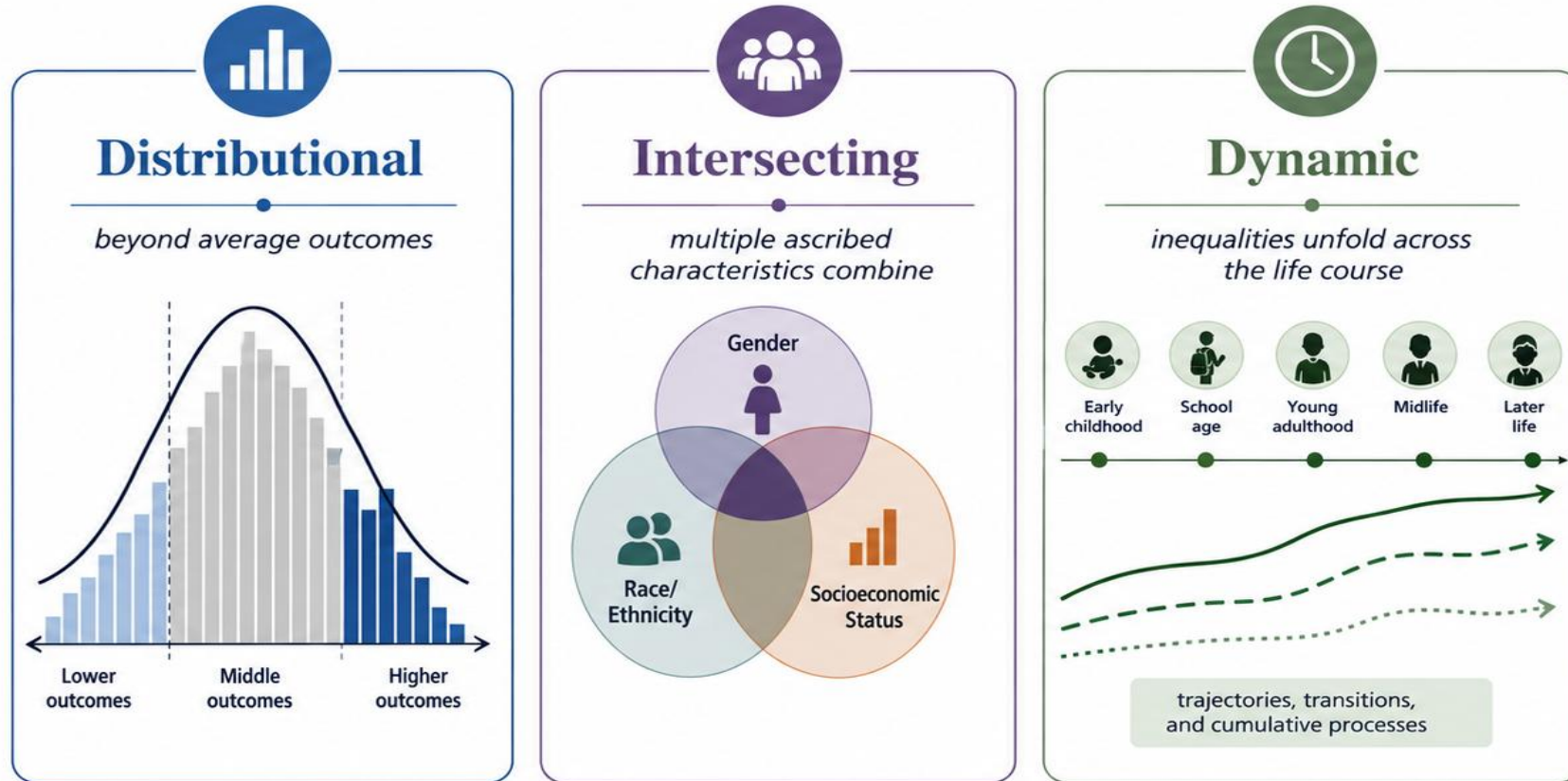
Improved data and methods allow us to study inequalities that are:



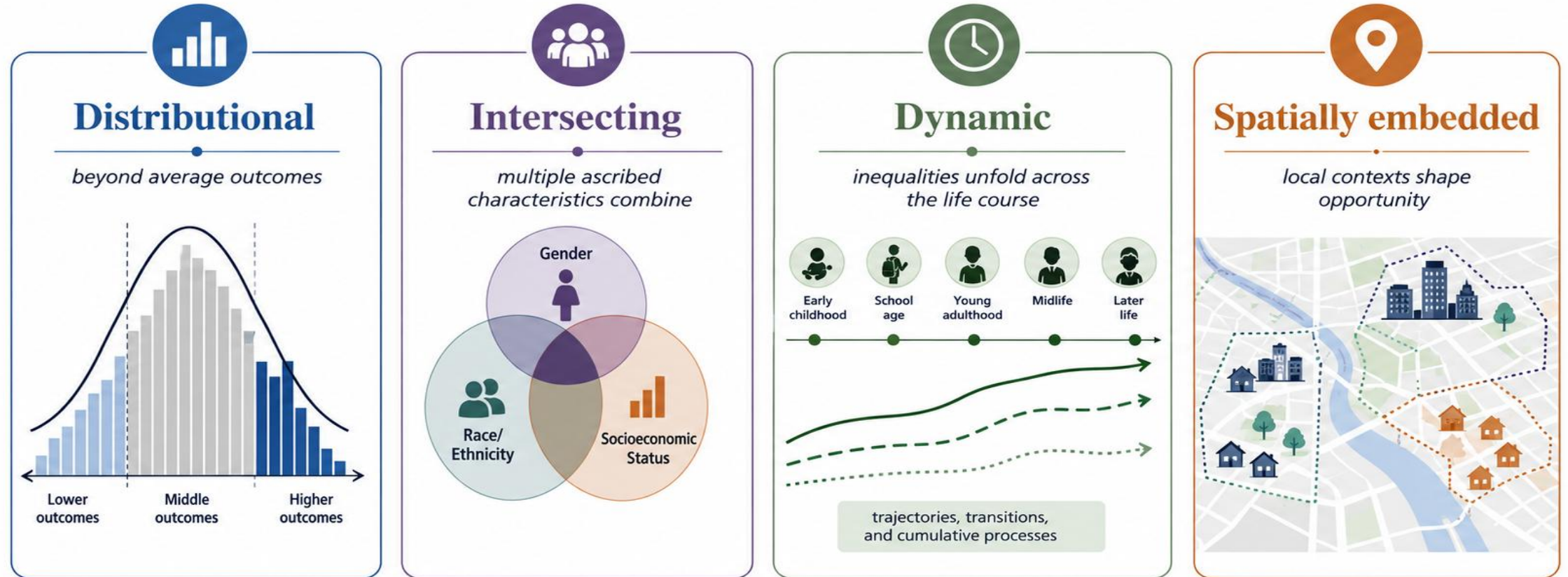
Improved data and methods allow us to study inequalities that are:



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Improved data and methods allow us to study inequalities that are:



Beyond averages

- Social inequalities are often not adequately captured by **mean differences alone**.
- Improved data and methods allow us to study how disadvantage is distributed across the **entire outcome distribution**: lower tail, middle, upper tail
- This makes it possible to distinguish between: **poverty/floor effects, median shifts, top-end concentration or polarization**

The key question is no longer only “who does better on average?”, but also “where in the distribution does inequality matter most?”

(Di Nardo et al 1996; Firpo et al 2009; Reardon 2011; Chernozhukov et al. 2013)

Example: gender earning gaps among recent PhD graduates

Data: ISTAT Italian survey on PhD Graduates

Years: 2009 (2004), 2014 (2009)

Methods: KOB and RIF regressions and decompositions

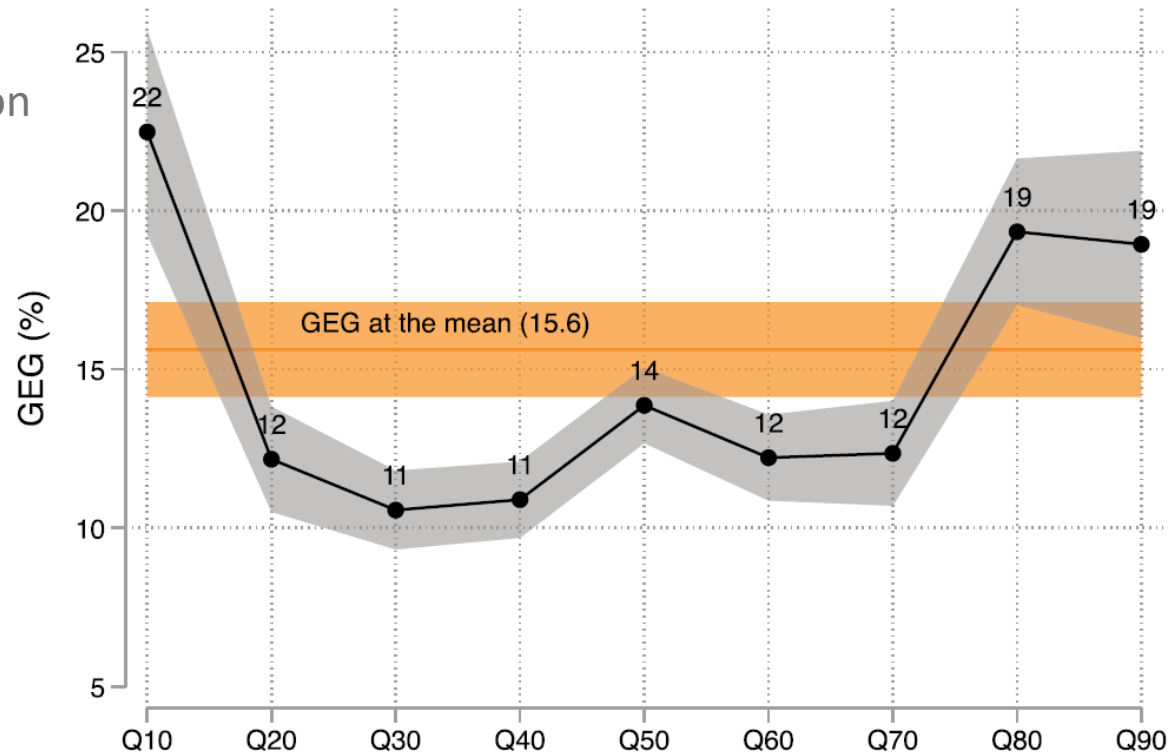
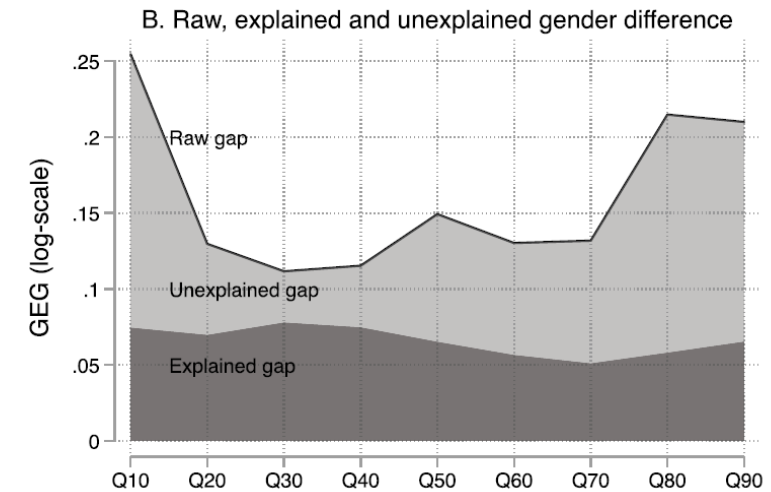


Fig. 1. Raw gender earnings gap (% change) at the mean (orange line) and along quantiles (black connected dots) of the unconditional distribution. Note: women's penalty is computed as a percentage difference between the earnings of women and men.



(Passaretta & Triventi 2023 RSSM)

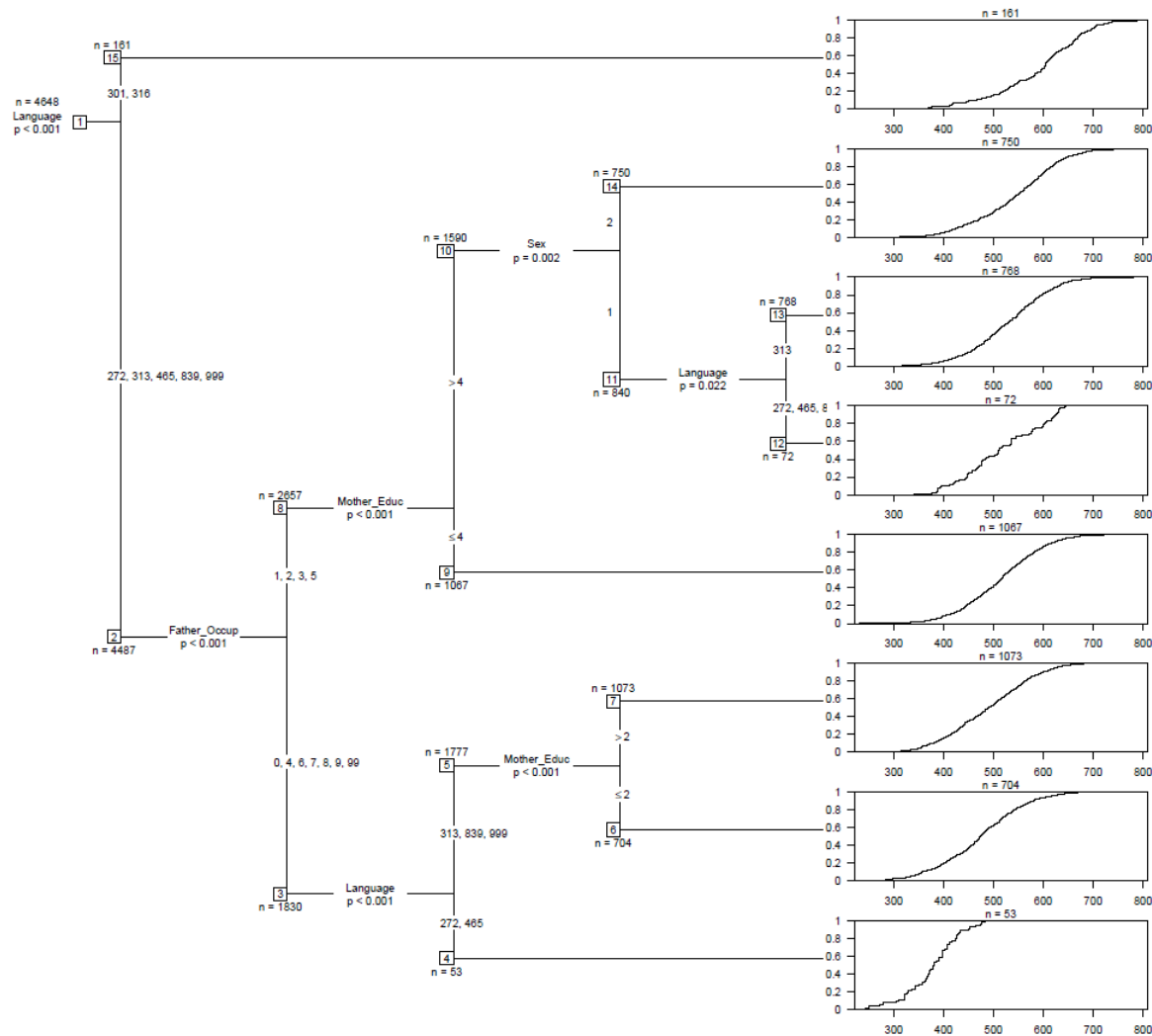
Beyond single dimensions of stratification

- Social inequalities are rarely structured by a single ascribed characteristic
- Improved methods allow us to study how **multiple dimensions** of disadvantage **combine and interact**, rather than treating them as merely additive
- A **quantitative intersectional approach** helps identify which combinations of circumstances are most strongly associated with unequal life chances

The issue is not only whether class, gender, or ethnicity matter, but when and how they matter together and reinforce each other

(Else-Quest and Hyde 2016; Steinmetz & Guarnerio 2026)

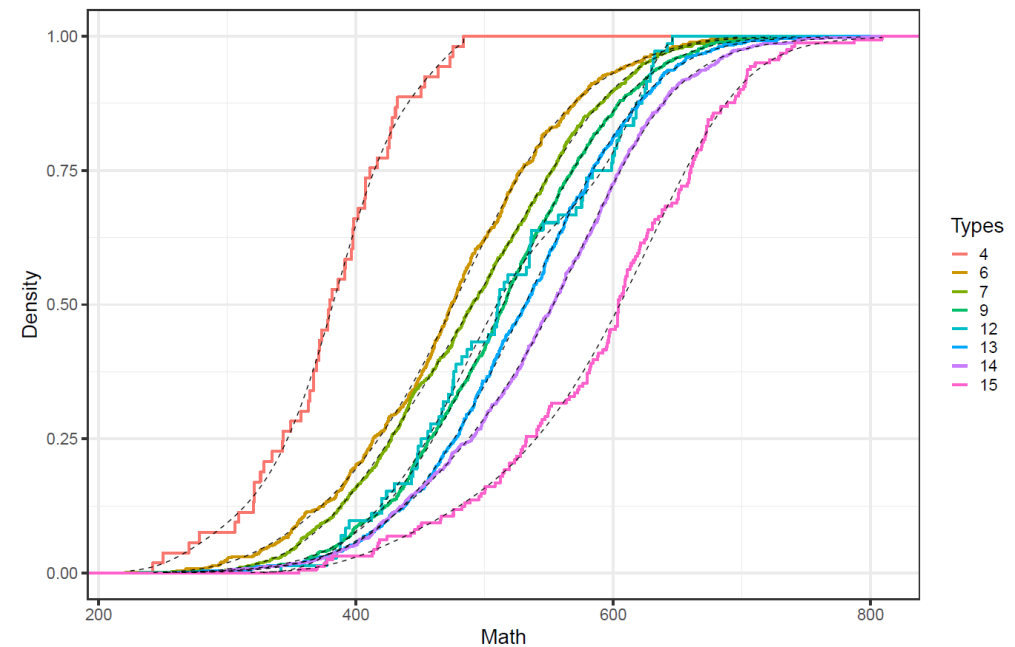
Example: competencies inequality using transformation trees and ECDF – New Zealand



Data: OECD PISA

Years: 2000-2022

Methods: machine learning (transformation trees)
(Hothorn & Zeileis 2021)



(Brunori, Gil-Hernandez & Triventi 2025,WP)

Beyond snapshots

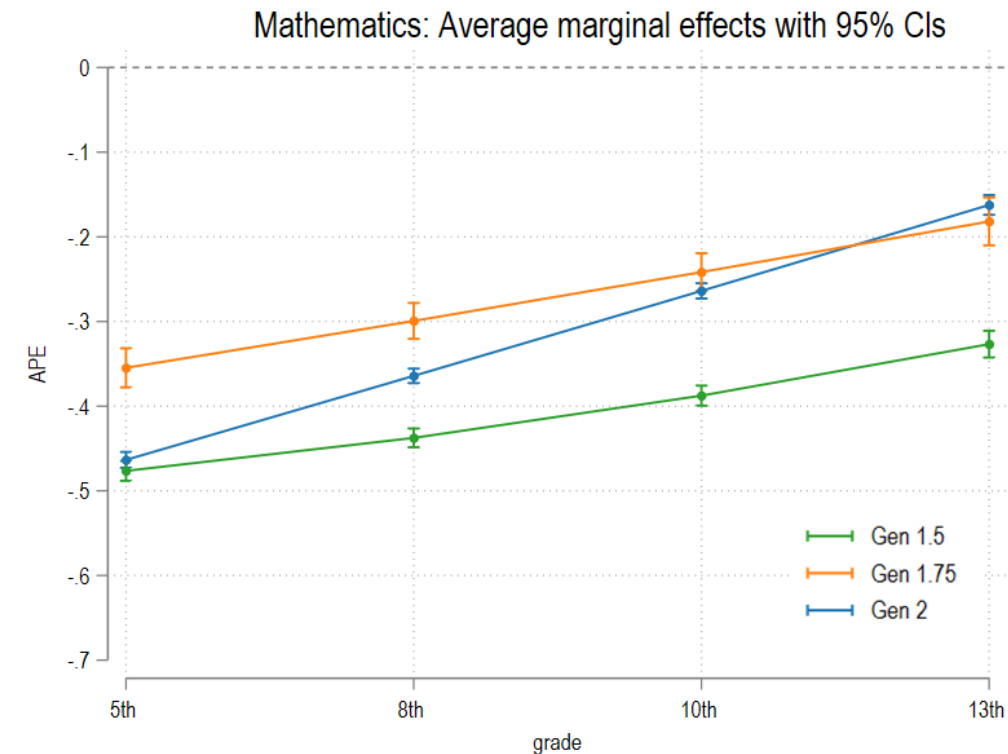
- Inequalities are not only static differences in outcomes
- They are also **dynamic processes** unfolding over time
- Improved longitudinal and administrative data allow us to study **trajectories, transitions, timing, turning-points**
- It allows to study cumulative disadvantages across the life course

The key question becomes not only who gets what, but when, through which sequence, and with what cumulative consequences

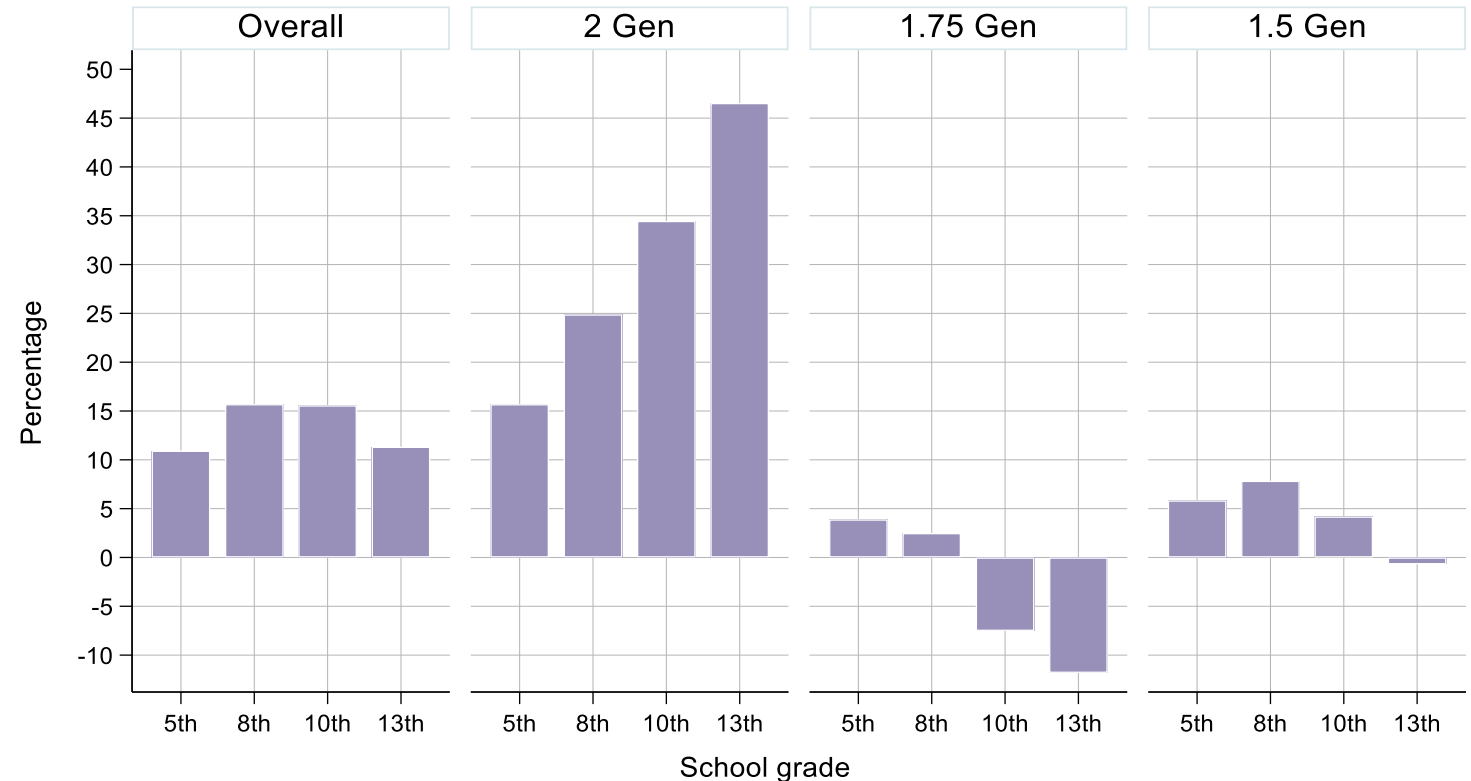
(Elder 1994; Dannefer 2003; DiPrete and Eirich 2006; Mayer 2009)

Math achievement gaps by migration background along the educational career

Achievement gaps vs natives (SD)



% of the gap with natives explained by family socio-economic position



Data: INVALSI Italian student population data

Years: 2013-2021

Methods: growth curve models + dynamic KOB decomposition

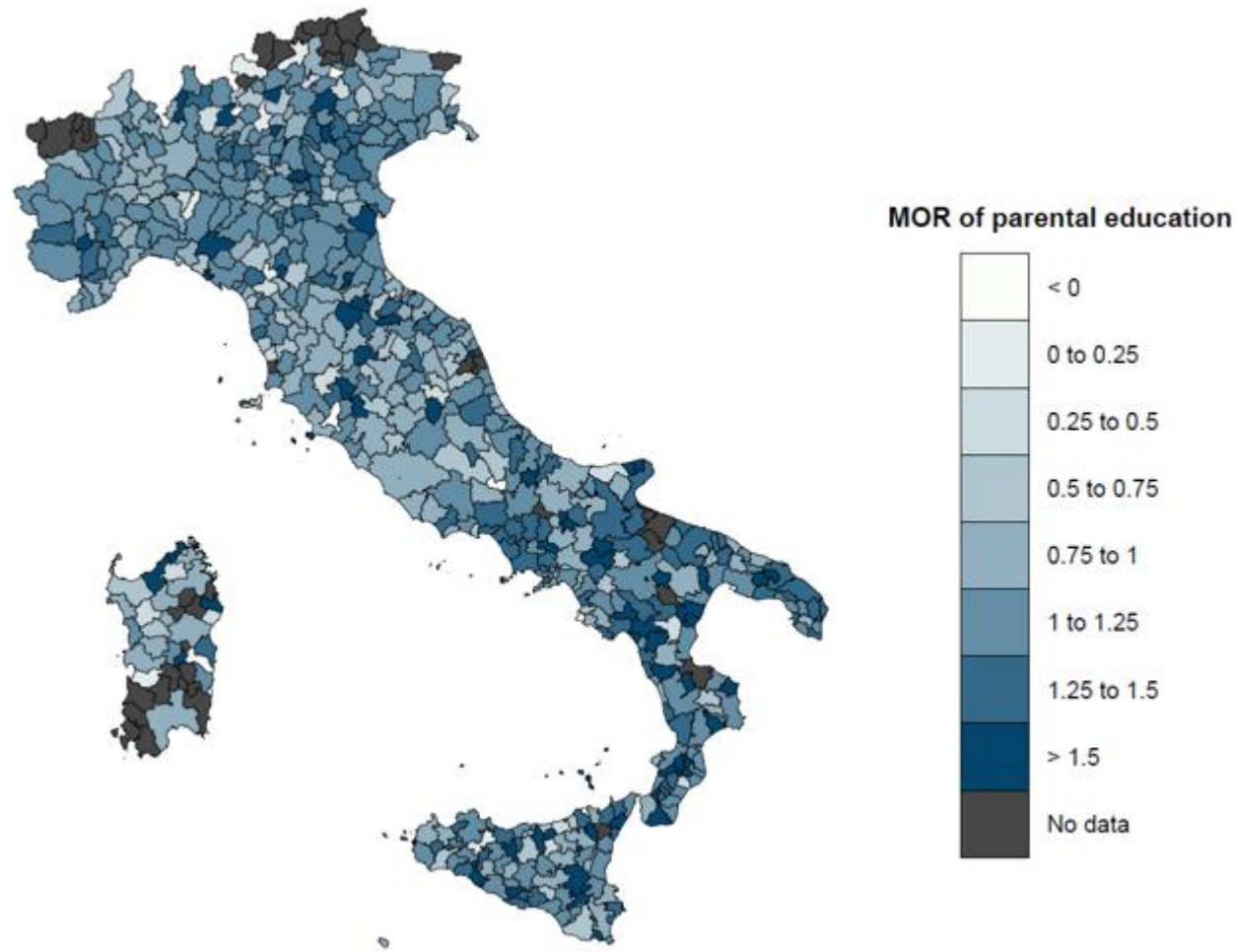
(Fiasconaro, Salza & Triventi 2026, WP)

Beyond national aggregates

- Inequality is not only distributed across individuals, but also **organized across places**
- Improved geocoded and linked data allow us to move **beyond methodological nationalism** and study inequalities within countries
- This makes it possible to identify how **local opportunity structures** shape life chances through institutional quality, segregation, peer environments, services, and infrastructure.

Place is not a residual background condition; it is part of the mechanism through which inequalities are generated

Example: Within-country variation in inequality in academic track enrolment by social background in Italy



Data: INVALSI Italian student population data

Years: 2013–2017; 1,344 million students from five cohorts in 541 labor market areas

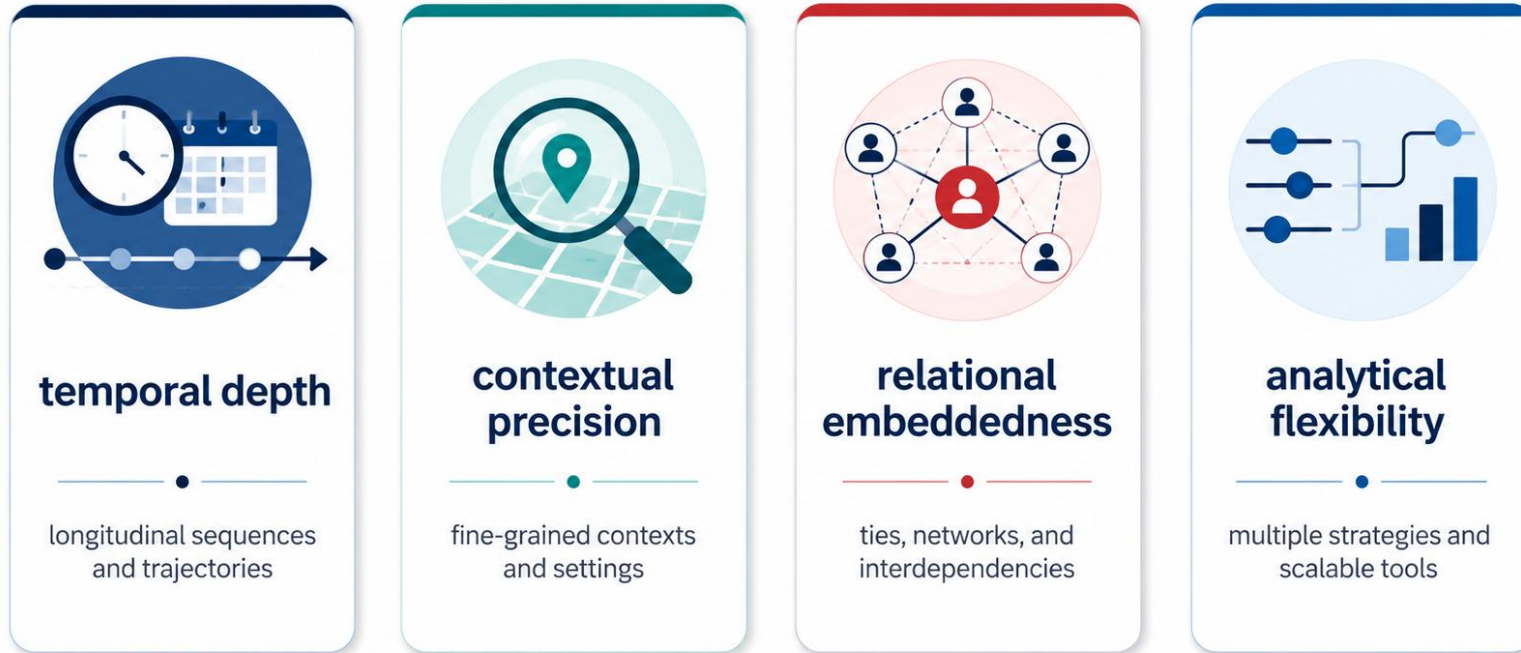
Methods: binomial logistic regression models + marginal odds ratios

Differences between North, Centre, and South account for less than 5% of the total variation in MORs across local areas

(Triventi, Vigna, Pietrolucci & Fedeli, 2026)

More than “more data”

What changed is not only scale. We now have greater:



This expands the sociological questions we can answer

(Connelly et al. 2016; Small 2023)

1.2 Challenges of an expanded field

The Challenges of an Expanding Field

Four risks that accompany new data and new methods



(Edelmann et al. 2020; Foster et al 2021; Small 2023)

The Challenges of an Expanding Field

Four risks that accompany new data and new methods

Shared
Questions

Data
triangulation



Theory-
driven
designs

Integrated
analytical
tools, micro-
macro links

Part III - Where Should We Go?

Building a Cumulative Social Stratification Research
Programme

2.1 Theoretical opportunities

Opportunity 1: rebuild cumulative knowledge around shared questions

Five shared questions to organize the field

SHARED QUESTION



1. WHO GETS WHAT?

Which groups experience advantages or disadvantages?



2. THROUGH WHICH MECHANISMS?

What processes generate these differences?



3. UNDER WHICH CONDITIONS?

When and where are the inequalities stronger or weaker?



4. WITH WHAT INTERGENERATIONAL CONSEQUENCES?

How are advantages or disadvantages transmitted?



5. WHAT CAN REDUCE INEQUALITY?

Which interventions can narrow the gaps?

Opportunity 1: rebuild cumulative knowledge around shared questions

Five shared questions to organize the field

SHARED QUESTION	EXAMPLE 1: EDUCATION <i>Why do children from advantaged families achieve more?</i>	EXAMPLE 2: HEALTH <i>Why do disadvantaged groups have worse health and shorter lives?</i>
 1. WHO GETS WHAT? Which groups experience advantages or disadvantages?	 Children from highly educated families obtain higher test scores and are more likely to obtain a university degree.	 People with lower socioeconomic status have shorter life expectancy and more chronic conditions.
 2. THROUGH WHICH MECHANISMS? What processes generate these differences?	 Economic resources (e.g., ability to afford books, tutoring) and parental involvement in learning.	 Material deprivation and chronic stress leading to unhealthy behaviors and limited access to quality care.
 3. UNDER WHICH CONDITIONS? When and where are the inequalities stronger or weaker?	 Stronger in highly stratified education systems; weaker where compensatory resources are provided in early childhood.	 Stronger in countries with larger income inequality and weaker social protection; weaker in universal healthcare systems.
 4. WITH WHAT INTERGENERATIONAL CONSEQUENCES? How are advantages or disadvantages transmitted?	 Higher education leads to better jobs and earnings, which benefit the next generation through resources and aspirations.	 Poor health limits educational and economic opportunities and increases the risk of poor health for the next generation.
 5. WHAT CAN REDUCE INEQUALITY? Which interventions can narrow the gaps?	 High-quality early childhood education and targeted academic support for low-income students.	 Strengthen primary care and preventive services; reduce income poverty through cash benefits.

Opportunity 2: Continue to embed empirical research in solid theoretical work

What good theory should do

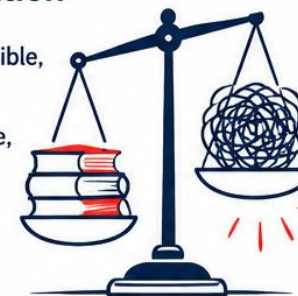
1. Go beyond common sense

Challenge taken-for-granted assumptions and reveal what is not obvious.



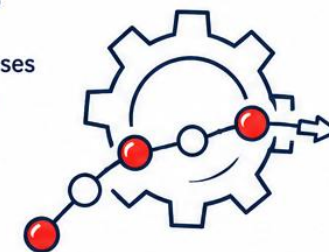
2. Avoid sterile overcomplication

Be as simple as possible, but no simpler.
Parsimony is a virtue, not a limitation.



3. Specify mechanisms

Identify the processes and pathways that connect causes to outcomes.



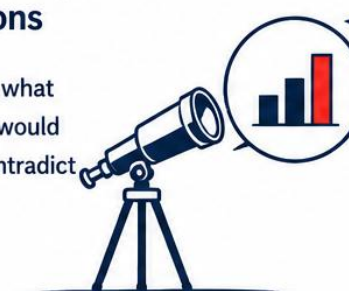
4. Generate testable propositions

Translate theory into clear, testable hypotheses that can be confirmed or refuted.



5. Clarify empirical implications

Make explicit what observations would support or contradict the theory.



6. Specify scope conditions

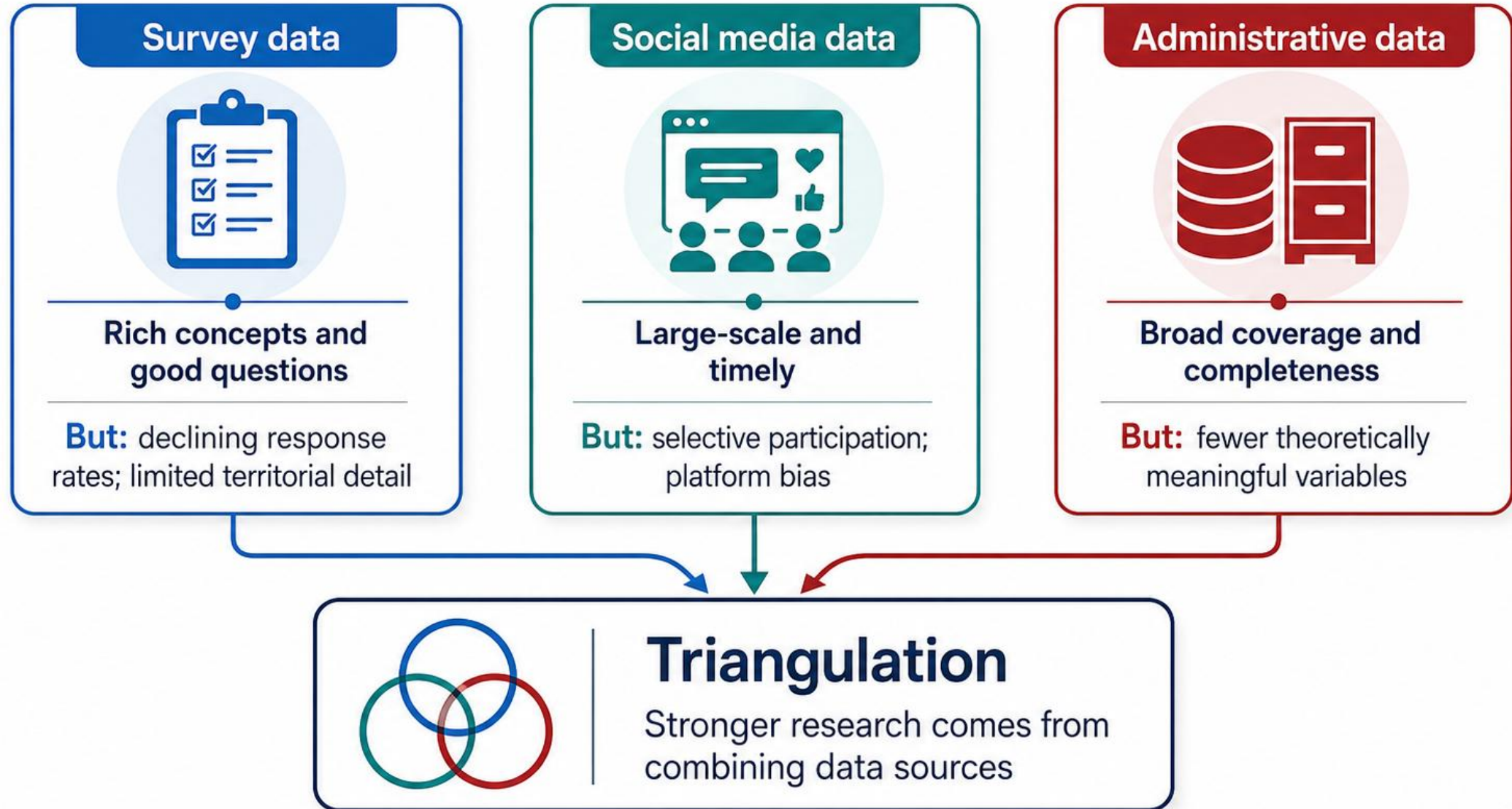
State where, when, and for whom the theory is expected to hold.



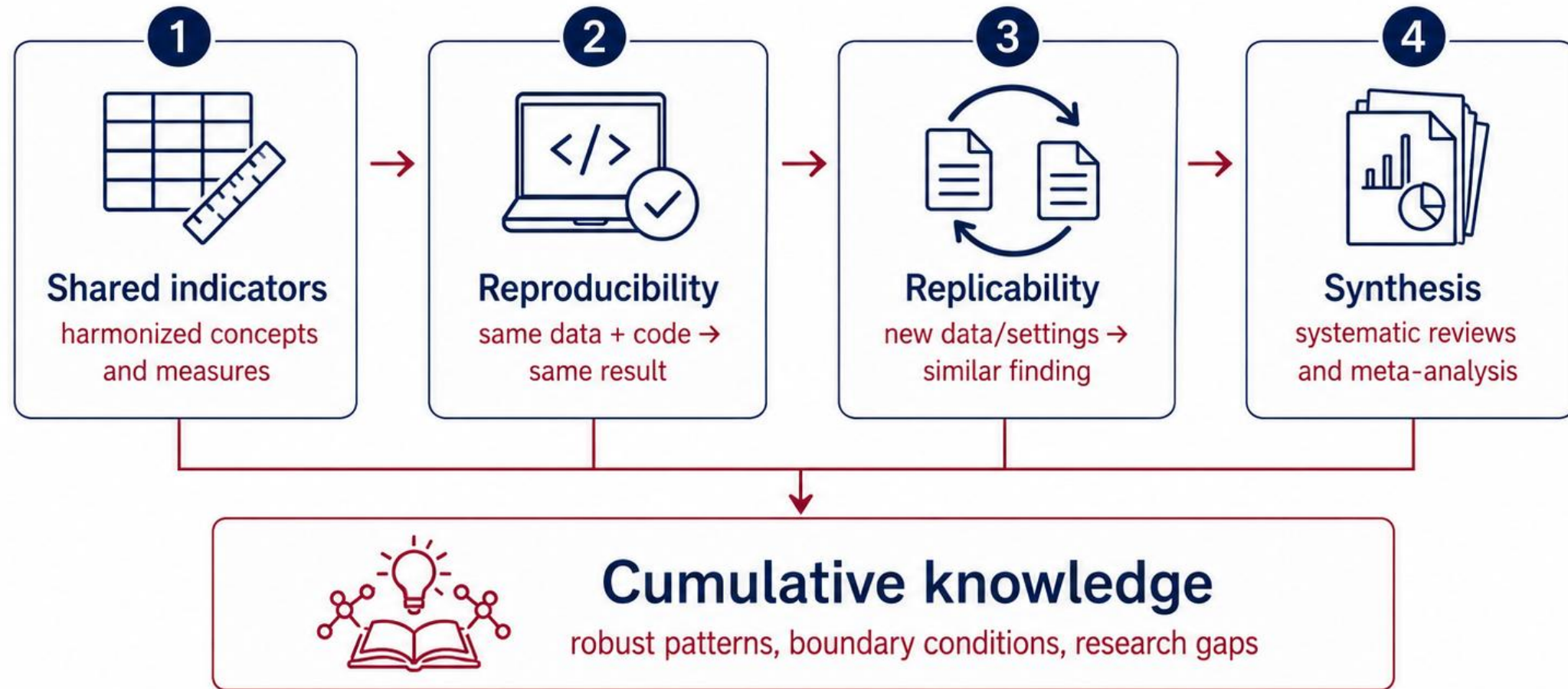
Good theory doesn't just explain the past.
It guides *inquiry*, structures *evidence*, and travels *beyond* the case at hand.

(Coleman 2000; Raub et al. 2011; Duncan 2014; Healy 2017; Goldthorpe 2016)

Opportunity 3: data triangulation



Opportunity 4: synthesis and reproducibility



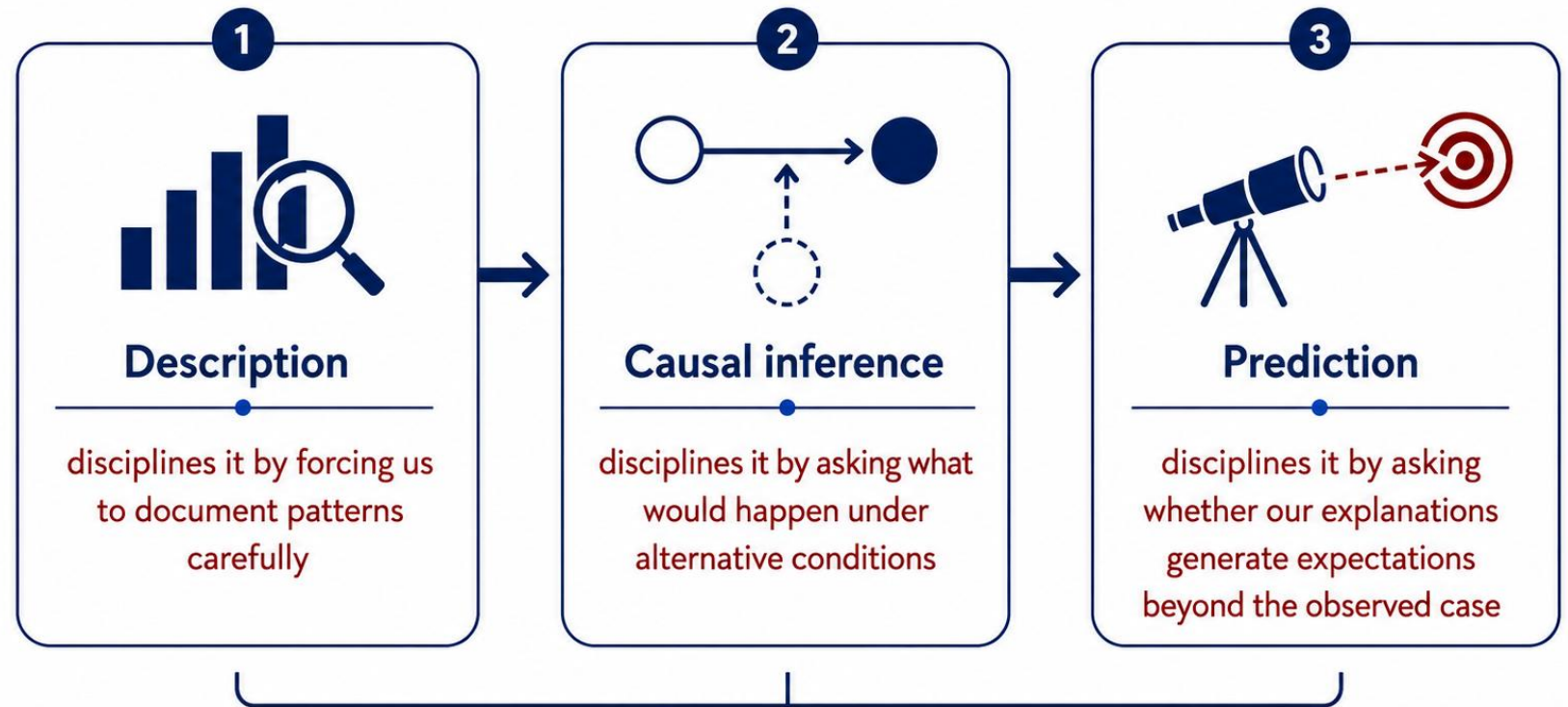
More data become more useful when results are comparable, reproducible, and synthesizable.

Opportunity 5: integrated analytical tools

Three analytical tasks

How to improve the rigor of the tests of our explanations?

How to avoid post-hoc explanations due to undisciplined sociological imagination?



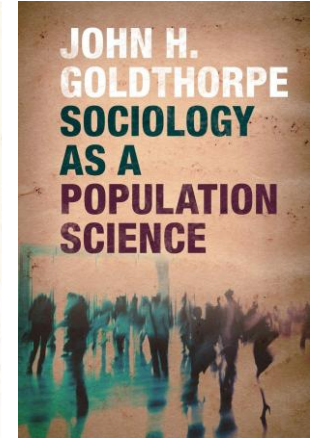
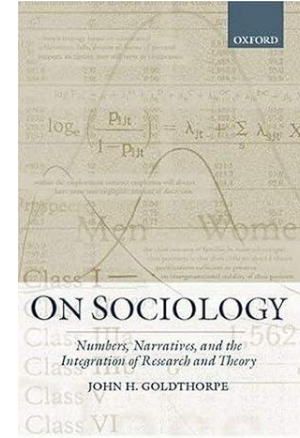
Three complementary tasks in one analytical program

(Shmueli 2010; Ito et al. 2025)

3.1 Patterns of inequality: the indispensable role of *description*

Description remains indispensable

- Descriptive research is one of the major strengths of stratification scholarship.
- It is crucial for:
 - identifying gradients,
 - mapping variation,
 - documenting new forms of inequality,
 - locating where disparities are greatest.
- In this field, good description is not “mere description”: it often provides the **empirical foundation for explanation**.
- But description alone cannot tell us which mechanisms generate the observed patterns, or which interventions might change them.



(Goldthorpe 2000; 2016)

...but it should not be a substitute for poor research designs
and to avoid causal explanation



If the theoretical argument implies a causal relationship, the empirical design should try to estimate it on the basis of assumptions that allow a credible causal interpretation

[AJPH PUBLIC HEALTH OF CONSEQUENCE](#)

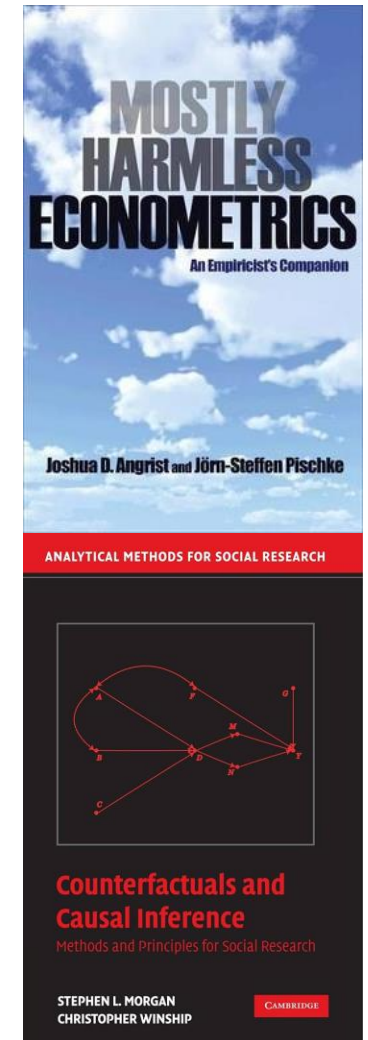
The C-Word: Scientific Euphemisms Do Not Improve Causal Inference From Observational Data

(Hernan 2018)

3.2 From Patterns to Causes

From description to (causal) explanation

- Description tells us **where** inequality is, **how large** it is, and **how it varies**.
- But it leaves open harder questions:
 - **why** these patterns emerge
 - **which mechanisms** generate them
 - **what would change** under different conditions or interventions
- The **counterfactual model** offers a disciplined way to move from observed disparities to **causal questions**.



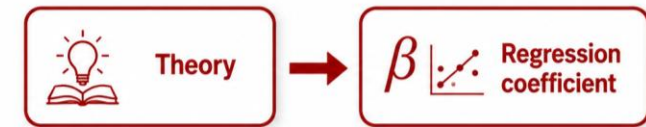
(Angrist and Pischke 2010; Morgan & Winship 2017)

The potential of the counterfactual model

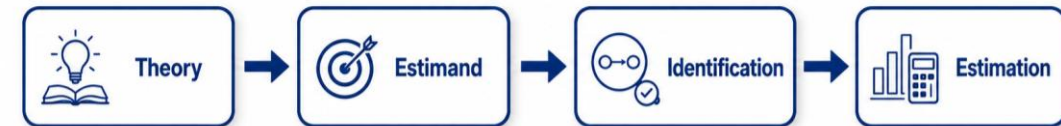
It forces researchers to specify:

- **The causal question**
 - What effect do we want to estimate?
- **The quantity of interest**
 - Which causal estimand?
- **The research design (identification strategy)**
 - How can we approximate the counterfactual?
- **The assumptions**
 - Under what conditions is estimation possible?

Move from:



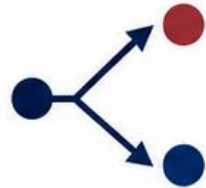
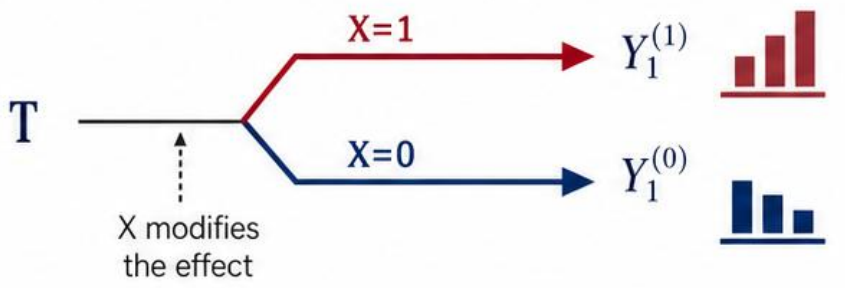
To:



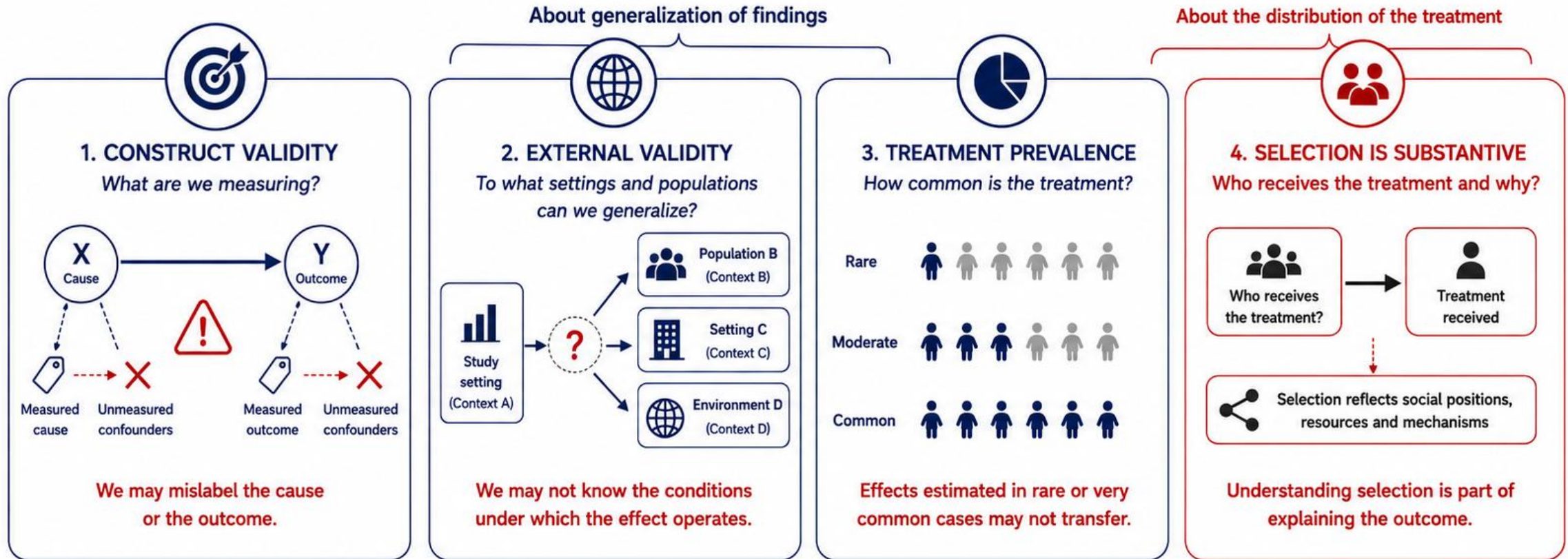
(Lundberg et al. 2021; Keele et al. 2022)

Applying the causal framework to inequality studies

X = ascriptive characteristic; Y = outcome; M = mediator; T = treatment or policy

Application	Conceptual scheme	Formula
 Total gaps Descriptive disparity		$E[Y X = 1] - E[Y X = 0]$
 Direct effects Residual inequality		$NDE = E[Y_{1,M0} - Y_{0,M0}]$
 Indirect effects Mediation / mechanisms		$NIE = E[Y_{1,M1} - Y_{1,M0}]$
 Heterogeneous effects Intersectional inequality / differential responsiveness		$CATE(x) = E[Y_1 - Y_0 X = x]$ $\text{Effect}(T \rightarrow Y X = 1) \neq \text{Effect}(T \rightarrow Y X = 0)$

Improved causal inference: beyond internal validity alone

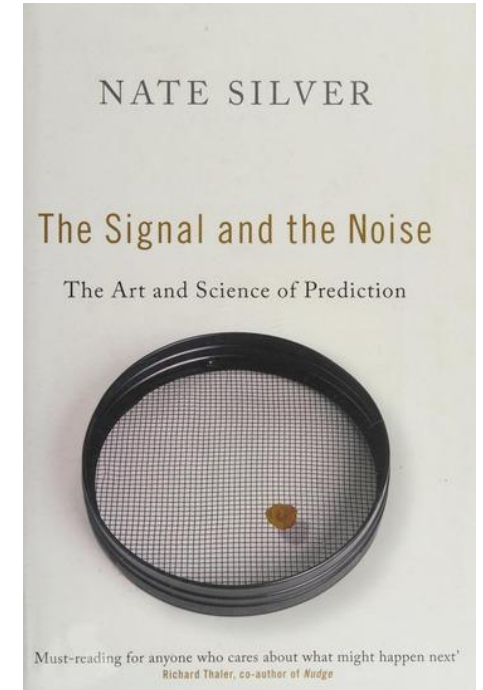


(Esterling et al. 2025; Pietrzyk & Jacob 2026; Williams 2026)

3.3 Prediction as a Test of Explanation

Prediction as a discipline for explanation

- Prediction should not be treated as the opposite of explanation.
- A convincing explanation should imply what we would expect under different conditions or in new cases.
- Prediction helps distinguish:
 - Signal from overfitting
 - Well-grounded theoretical explanations from ex-post rationalization

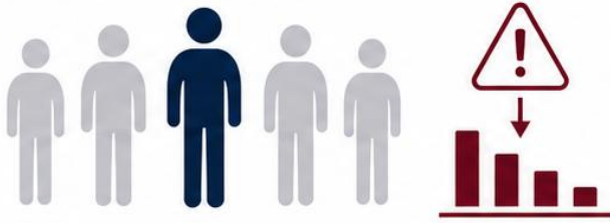


Prediction is one of the most demanding tests of explanatory quality

(Hempel 1965; Shmueli 2010; Silver 2012; Duncan 2014)

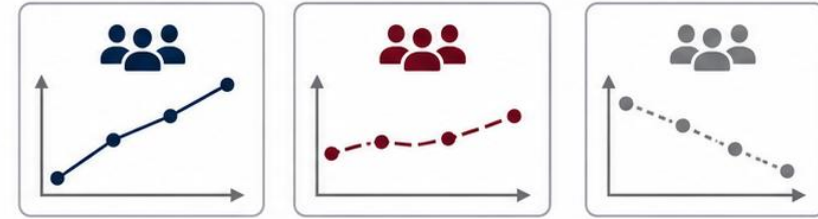
What prediction can do in inequality research

1 Measure structured disadvantage



Predict who is most exposed to risks or lower resources.

2 Detect heterogeneity



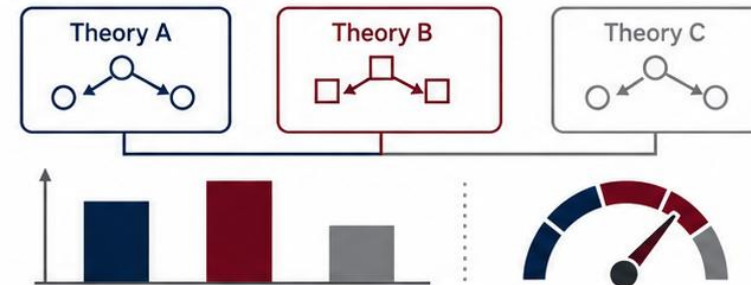
Test whether predictive patterns differ across groups or contexts.

3 Test generalization



See whether a model travels across cohorts, countries, or settings.

4 Compare mechanisms



Compare predictive power of models based on different theories.

Used in this way, prediction becomes a tool for measurement, diagnosis, and theory-testing

A better integration of description, prediction, and causal evidence



Description tells us where inequality is, how large it is, and how it varies.



Prediction tells us how strongly outcomes are structured, where heterogeneity matters, and whether explanations travel beyond the sample.



Causal inference tells us whether changing a condition, exposure, or policy would plausibly change the outcome.

A stronger inequality research programme should combine all three, rather than treating them as competing paradigms

(Lundberg et al. 2021; Brand, Zhou, and Xie 2023; Molina and Garip 2019)

Example: SES, ECEC participation and children's early competencies

1. To what extent are there SES gaps in early children cognitive and socio-emotional competencies?
2. To what extent ECEC attendance can mitigate this gap?

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<https://doi.org/10.1093/esr/jcac048>

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Original Article

OXFORD

Is early formal childcare an equalizer? How attending childcare and education centres affects children's cognitive and socio-emotional skills in Germany

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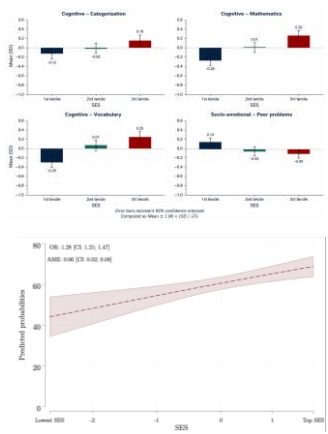
*Corresponding author. Email: gaia.ghirardi@eui.eu

An integrated research design

Description

Main patterns

- SES gap in competencies
- SES gap in ECEC participation



Causal inference

Identification

- DAG + assumptions
- Clear definition of the ‘treatment’

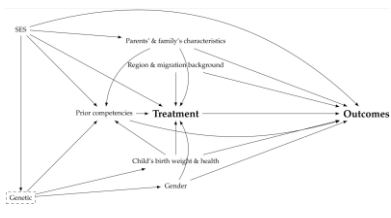
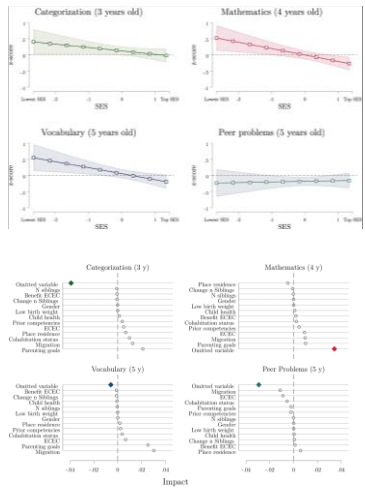


Table 1. Definition of ECEC attendance

	ECEC attendance
ECEC only	1
ECEC and informal care	Excluded
Informal care	0
Parental care only	0
Family day care (only or plus informal care)	0

Estimation

- IPW regression + sensitivity analysis
- Positive effects of ECEC attendance concentrated among low SES



Prediction

Counterfactual predictions

- SES gaps in competencies would shrink but not completely eliminated under universal attendance scenario

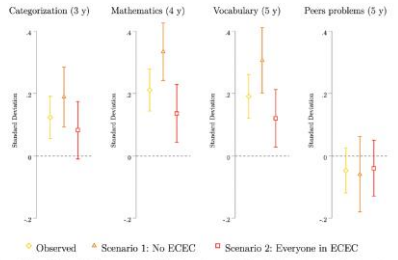


Figure 6. Effect of SES on children's competencies (in SD) at the actual rates of ECEC participation and two counterfactual scenarios. Notes: n = 992. Controlled for gender, n. of siblings, change in siblings, region, migration background, cohabitation, mother's expectation of ECEC for children development, parenting goals, child's health, birth weight, prior competencies. Source: doi: 10.5167/NEPS-SCI-8.0.0, own calculations.

3.4 From Understanding Inequality to Reducing It

Policy (irr)relevance?



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Research in Social Stratification and Mobility 24 (2006) 1–20

Research in Social
Stratification and
Mobility

<http://elsevier.com/locate/rssm>

What we have learned: RC28's contributions
to knowledge about social stratification

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Received 23 July 2004; received in revised form 5 October 2005; accepted 31 October 2005

RC28 probably needs two agendas for the future. As Yossi Shavit pointed out at the Libourne meeting in 2000, we have very little to say to policy-makers. Our work looks inward to the academic concerns of the community of scholars that makes up the RC. An attempt to translate even a few of the 19 generalizations we discussed into guides for social policy would be very valuable. Or it might be impossible. If RC28's work does not translate into recommendations to policy, we ought to figure out how to get ourselves from the generalizations spelled out here to the ideas with practical value.

Socius: Sociological Research for a Dynamic World



Open access | CC BY-NC-ND | Research article | First published online June 15, 2021

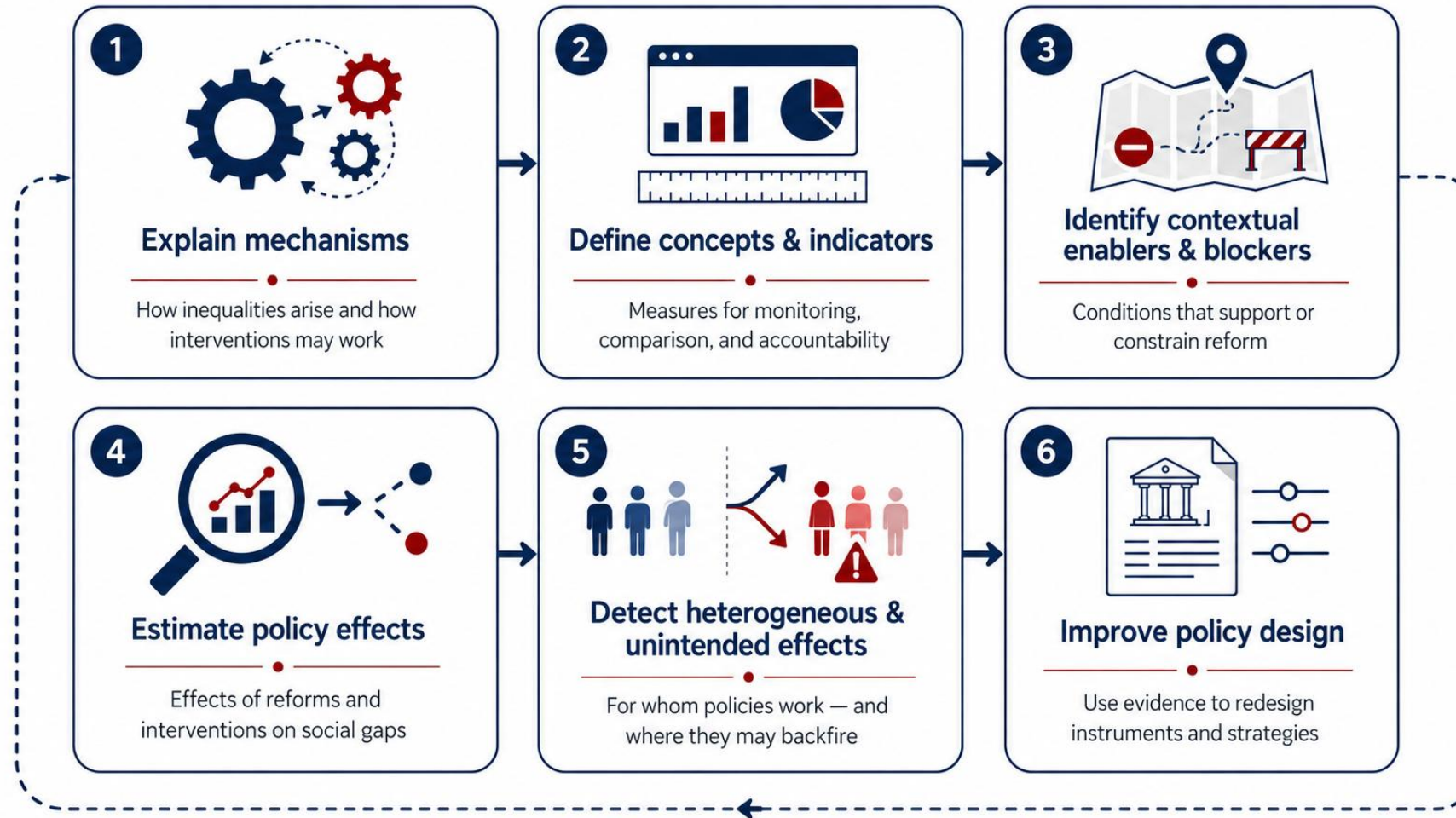
Sociology's Role in Responding to Inequality: Introduction to the Special Collection

[Adam Gamoran](#) [View all authors and affiliations](#)

What has been sociology's role in responding to inequality? By one reckoning, not much. Sociology has excelled in aiding our *understanding* of inequality: how much inequality exists, what its sources are, and what consequences ensue. But sociology as a discipline has contributed far less to *reducing inequality*, that is, to identifying the specific programs, policies, and practices that must be undertaken to change the course of inequality in the United States and elsewhere.

Stratification research is often much better at diagnosing inequality than at identifying feasible levers for reducing it

How can social stratification inform policies?



(Gamoran 2022; Van de Werfhorst 2022)

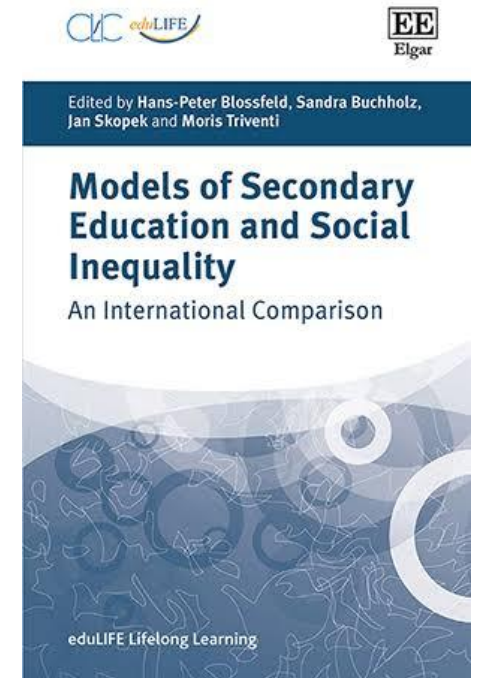
Example: advantage finds its way

Evidence

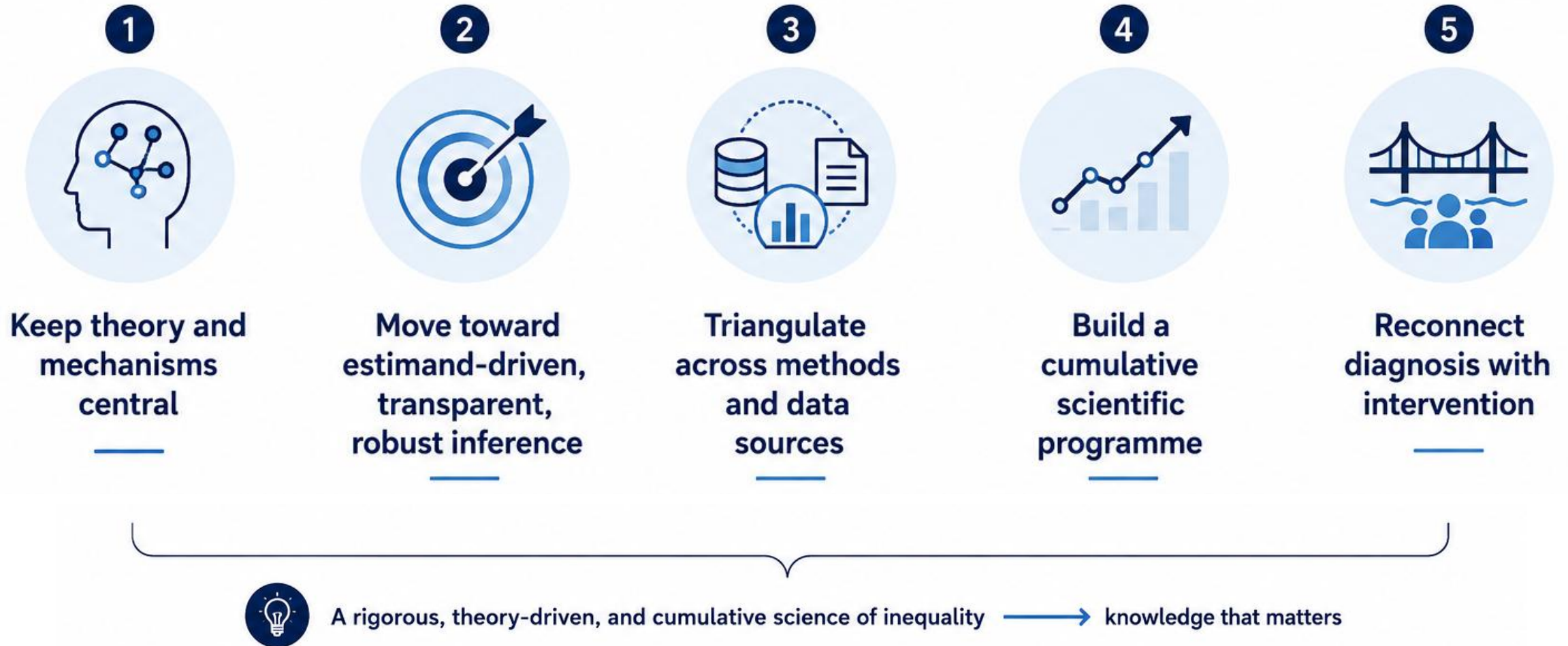
- Similar inequalities across very different school systems.
- Privileged families exploit available opportunities.
- Hidden differentiation matters.

Policy lesson

Reforming institutions is not enough; policies must address the mechanisms through which advantage is reproduced.



Conclusion and agenda: what kind of field should we build?





Thank you!



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