ME01: Rethinking Explanation, Causality, and Prediction in Social Science

10:50 - 12:30 Saturday, 20th June, 2026
Room Olympic (ICC)

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13 Rethinking Explanation, Causality, and Prediction in Social Science

Description

Across the social sciences, causality has become an organizing principle but also a polarizing force in research methodology. Entire research programs now pivot on identifying causal effects, which some argue has led to the expense of broader explanatory or theoretical ambitions. This panel brings together work that takes on these questions by pointing to novel ways of gaining credible, generalizable, and meaningful social inquiry.

At the center lies a shared question: What does it mean to learn from data? The papers approach this from different angles—rethinking how uncertainty can be measured and preregistered rather than merely controlled; how the accumulated record of studies might be reanalyzed to reveal generalizable patterns; how prediction can serve as a route to stronger theory rather than a substitute for it; and how the very concept of causality has drifted from a theoretical ideal into a methodological end in itself.

Taken together, these interventions suggest that methodological innovation is necessary to balance competing goals of research design. To move forward, these methods help make causality, prediction, and description as complementary methods that aim for the full explanation of complex human realities.

Chair

Matthew Loveless
University of Bologna, Italy

Discussant

Constantine Boussalis
Trinity College Dublin, Ireland

Categories

Political Methodology

288 Death by Assumption: How an Obsession is Slowly Killing Social Science

Matthew Loveless
University of Bologna, Italy

Abstract

Social science aims to explain human behavior. Yet, an obsession with causality has turned a vital theoretical concept into a statistical fixation. This is the basis for a book project that charts the intellectual history of causality - from theoretical tool to methodological result - and how it became the exclusive criterion for ‘good social science.’ Building on long-standing critiques of causality’s oversized role, I propose recalibrating the aims of social science back to *scientific explanation*. This is not a Perestroika attack on causality but rather an intervention of perspective for the scope and aims of social science. It offers a constructive framework - beginning with questions rather than methods - that merges causality and prediction (as well as description) - to do so. This book will speak both to specialists and to the broader public concerned less with technical puzzles and more with how social science can reclaim its core purpose: making sense of complex human realities.

Section

Political Methodology

309 Holistic Causal Learning with Causal Graphs: A Credible Method for Study Design And Preregistration in the Social Sciences

Robert Kubinec
University of South Carolina, USA

Abstract

While research designs in the social sciences have employed increasingly sophisticated methods to control false positive rates, there is still substantial debate about the merit of pre-registration and other recent open science reforms. In this paper, I present a method for preregistering causal graphs and employing the metric of entropy, and in particular Jaynes' theory of maximum entropy, to propose a holistic way of measuring the contribution of a research study. To demonstrate the method's utility, I show how recent research in both COVID-19 and political authoritarianism can be fruitfully understood using causal graphs and entropy. Additionally, I provide R code to enable researchers to compute these metrics, helping them prepare for various outcomes and learning approaches for the purpose of preregistration.

Section

Political Methodology

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308 Building Better Theories Through Prediction and Explanation

Chiara Binelli
University of Bologna, Italy

Abstract

With the availability of large datasets, prediction can be used to develop better theories of human behavior. Merging prediction with explanation and using it for theory building improves the very ability to explain reality. We develop an integrative modelling framework that combines supervised machine learning with causal inference to improve explanatory power, uncover new causal relationships, and strengthen theory robustness. In doing so, this new framework changes the way we do science from the research design to the empirical analysis in turn allowing to better understand behaviour. We provide an application of this approach by developing and estimating a model of climate change perceptions in the United States.

Section

Political Methodology

1808 Evaluating Evidence Support for Grand Theories of Politics Using AI Agents

Tore Wig
University of Oslo, Norway

Abstract

Many prominent political science theories are broad in scope, producing numerous empirical implications across diverse outcomes and domains—from war and democratization to legislation and elections. These Grand Theories lack

a single decisive test or causal estimand; instead, their credibility rests on cumulative evidence scattered across vast and heterogeneous literatures. Existing approaches to meta-scientific evaluation are ill suited for this task: qualitative reviews are too labor-intensive and subjective to cover the full body of relevant research, while quantitative meta-analyses of treatment effects or sensitivity analyses of coefficients are too narrow and indeterminate to capture distributed evidence for grand theories. We propose a new framework for evaluating the evidential strength of such theories, combining LLM-powered AI agents with Bayesian Evidence Synthesis. The framework uses coordinated AI agents to (a) deconstruct theories into empirical implications, (b) scan and summarize research literatures, (c) generate "Running Literature Reviews" for each implication, and (d) synthesize results into theory-level assessments. This concept note outlines a scalable, transparent, and replicable path toward automated theory evaluation in the social sciences.

Section

Political Methodology

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707 Opening the Black-Box: Explaining Predictions with Shapley Values for Political Science Research

Christy Coulson
London School of Economics and Political Science (LSE), United Kingdom

Abstract

Political scientists increasingly adopt complex non and super-parametric machine learning (ML) methods to make predictions because these algorithms demonstrate predictive fidelity by inductively modelling nonlinear, interactive relationships between variables. However, such models often lack interpretable parameters intrinsic to the fitting process and therefore offer little explanatory leverage. Although recent advances in ML aim to reconcile predictiveness and interpretability, few studies show how to apply these tools rigorously in social science settings. I introduce a model-agnostic approach — the Shapley value and its operationalisation, SHAP — widely used in computer science and industry but underutilised by political scientists. I focus on two applications: tasks where prediction is the primary objective, and settings where ML predicts individual treatment effects to estimate treatment-effect heterogeneity. I show that SHAP yields feature and observation-level explanations with explicit inferential bounds: observation-level explanations can substantively justify policy decisions, while feature-level explanations can help identify potential drivers of treatment effect heterogeneity. I illustrate these claims with three empirical demonstrations: predicting and explaining civil war onset, a series of treatment effect heterogeneity simulations, and a reanalysis of an influential political experiment.

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