McGill | Department of Epidemiology, Biostatistics and Occupational Health

EPIDEMIOLOGY

EPIDEMIOLOGY SEMINAR / WINTER 2021

THE DEPARTMENT OF EPIDEMIOLOGY, BIOSTATISTICS AND OCCUPATIONAL HEALTH, - SEMINAR SERIES IS A SELF-APPROVED GROUP LEARNING ACTIVITY (SECTION 1) AS DEFINED BY THE MAINTENANCE OF CERTIFICATION PROGRAM OF THE ROYAL COLLEGE OF PHYSICIANS AND SURGEONS OF CANADA

ALYSSA BILINSKI, MS

PhD Candidate in Health Policy
Harvard Graduate School of Arts and Sciences with a concentration in Evaluative Science and Statistics

Goldilocks and the Pre-Intervention Time Series: How Long is "Just Right" and the Parallel Trends Implications

MONDAY, 11 JANUARY 2021 / 4:00 pm – 5:00 pm - ZOOM LINK

ALL ARE WELCOME

ABSTRACT: Difference-in-differences (DID) and synthetic control methods (SCM) assume that if treatment and comparison groups were sufficiently similar prior to an intervention (e.g. "parallel trends"), researchers can use a comparison group to impute a treatment group's counterfactual trajectory. Previous work has characterized conditions under which these methods are unbiased or consistent as T approaches infinity, and cautioned against using pre-intervention time series that are too short. However, pre-intervention time series that are too long may also introduce bias when trends change. While empirical researchers must select a pre-intervention time series, there is a dearth of guidance regarding its ideal length. We argue that rather than focusing on parallel trends over a long time horizon, researchers should optimize prediction of the treatment group by the comparison group. Based on this criterion, we present an estimator that leverages time-series cross validation to select optimal pre-intervention period weights.
We show that our estimator is asymptotically unbiased under traditional assumptions. It also minimizes absolute or mean-squared error under more flexible assumptions about the stability of the data-generating process. In practice, our approach improves performance compared to other estimators in standard, empirically-calibrated simulation scenarios, even those with a relatively short number of pre-intervention time periods (i.e., more than 40% decrease in out-of-sample mean-squared error compared to DID, SCM, synthetic DID, and augmented SCM). We apply our method to re-analyze the impact of Massachusetts health reform on mortality.

OBJECTIVES:

1. To understand why pre-intervention time periods that are too long or too short may introduce bias into estimates of causal effects;

2. To understand how to apply data driven estimators to select the length of the pre-intervention time period;

3. To understand how these estimators reduce bias and mean-squared error compared to traditional estimators.

BIO: **Alyssa Bilinski** is a PhD Candidate in Health Policy at the Harvard Graduate School of Arts and Sciences, with a concentration in Evaluative Science and Statistics. Her research interests include methods for non-experimental causal inference, incorporating cost-effectiveness and affordability into health care decision-making, and identifying early warning signals to inform time-sensitive policy interventions. In the COVID-19 pandemic, she has worked with policymakers and researchers on projects including: short-term hospital forecasts during spring 2020; modeling to inform contact tracing, school re-opening, and surveillance; and quantification of excess mortality.
Alyssa graduated summa cum laude from Yale College with a BA in Political Science and received an MS in Medical Statistics with Distinction from the London School of Hygiene and Tropical Medicine as a Marshall Scholar. Prior to Harvard, she worked at Partners In Health and the Yale Center for Infectious Disease Modeling and analysis. Outside of research, she enjoys powerlifting and long aimless Saturday walks.