School of Mathematical and Statistical Sciences
Arizona State University

M E M O R A N D U M

DATE: 03/31/2023

TO: Faculty and Students

FROM: Professor(s) Paul R. Hahn

Chair/Co-Chairs of Demetrios Papakostas

Defense for the PhD in Statistics

Committee Members

Ming-Hung Kao
Robert McCulloch
Shiwei Lan
Shuang Zhou

DEFENSE ANNOUNCEMENT

Candidate: Demetrios Papakostas

Defense Date: Friday, April 14, 2023

Defense Time: 1:00 PM

Virtual Meeting Link: https://asu.zoom.us/j/3717111999

Title: Case Studies in Machine Learning of Reduced Form Models for Causal Inference

Please share this information with colleagues and other students, especially those studying in similar fields. Faculty and students are encouraged to attend. The defending candidate will give a 40 minute talk, after which the committee members will ask questions. There may be time for questions from those in attendance. But, guests are primarily invited to attend as observers and will be excused when the committee begins its deliberations or if the committee wishes to question the candidate privately.

ABSTRACT
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Abstract

We develop versatile modeling tools to estimate causal effects when conditional unconfoundedness is not immediately satisfied. We provide a brief overview of common techniques in causal inference, with a focus on models relevant to the data explored in later chapters. The rest of the dissertation focuses on the development of novel “reduced form” models which are designed to assess the particular challenges of data studied in the later chapters.

First, we explore the question of whether or not forecasts of bankruptcy cause bankruptcy. The question arises from the observation that companies issued going concern opinions were more likely to go bankrupt in the following year, leading people to speculate that the opinions themselves *caused* the bankruptcy via a “self-fulfilling prophecy”. We develop a Bayesian ma- chine learning sensitivity analysis to answer this question. In exchange for additional flexibility and fewer assumptions, our approach loses point identification of causal effects and thus we proceed by studying a wide range of plausible scenarios of the causal effect of going concern opinions on bankruptcy with a sensitivity analysis. Reported in the simulations are different performance metrics of the model in comparison with other popular methods and a robust analysis of the sensitivity of the model to mis-specification. Results on empirical data indicate that forecasts of bankruptcies likely do have a small causal effect.

Further, we study the effects of vaccination on COVID-19 mortality at the state level in the United States. The dynamic nature of the pandemic complicates more straightforward regres- sion adjustments and invalidates many alternative models. We comment on the limitations of mechanistic approaches as well as traditional statistical methods to epidemiological data. In- stead, we develop a state space model that allows us to study the ever-changing dynamics of the pandemic’s progression. In the first stage, the model decomposes the observed mortality data into component surges, and later uses this information in a semi-parametric regression model for causal analysis. Results are investigated thoroughly for empirical justification and stress-tested in simulated settings.

A unifying theme of these projects is that we study reduced form versions of typical struc- tural models for the data discussed in this dissertation. While studying reduced form models can come with the loss of full identification of estimands of interest, our modeling philoso- phy both relaxes the stringent assumptions of alternative structural models as well as affords greater fidelity when learning the underlying relations in the observed data.