Heterogeneous Treatment Effects and Efficient Policy Learning: Evidence from the Oregon Health Experiment*

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Abstract

One of the primary objectives of any field experiment or quasiexperiments is to understand whom to treat. However, identical policy intervention distinctly affects individuals and subpopulations. Policymakers prefer to learn heterogeneous treatment effects to understand the underlying mechanisms that drive the results and to design targeted policy. I use the Oregon health insurance experiment data to estimate heterogeneous treatment effects of insurance on health outcomes. Then, I propose insurance assignment strategies constraining for ethical, legislative, and political reasons that can maximize the overall welfare.

Keywords: Insurance, causal inference, machine learning

JEL Classification: XXX, XXX

Note: This version is requesting feedback for the introduction section.

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1 Introduction

As of May 13, 2019, 37 states and the District of Columbia have expanded the Medicaid coverage to the low-income adults to 138% of the federal poverty level through the Affordable Care Act (ACA). The provision to expand health coverage to low-income adults via the Medicaid program through the Affordable Care Act (ACA) has triggered a substantial nationwide debate among policymakers and diverse stakeholders concerning what effects - if any - insurance coverage has on the various dimension of health care, well-being, health, and personal finances. Though states face a decision[1] about whether to adopt the Medicaid expansion or not, but the idea that the law's replacement might lead to millions of Americans losing coverage has brought this question into sharp focus.

Extensive literature studying the impact of insurance coverage on health outcomes report average treatment effects. However, establishing causal effects is challenging due to endogeneity. Endogeneity arises because it is difficult to control for observed and unobserved confounding variables among the insured and uninsured population (Levy and Meltzer, 2008). For example, a comparison of the health between those with and without health insurance, can exhibit that insurance is detrimental for one's health (Baicker and Finkelstein, 2011) because people with poor health are more likely to get insurance compared to healthy people.

A Random assignment of insurance can circumvent such confounding problems (Finkelstein et al., 2012), and the Oregon Health Insurance Experiment renders a unique opportunity to evaluate the causal effects of owning health insurance (Baicker and Finkelstein, 2011) on health and personal finance-related outcomes. In early 2008, Oregon's Department of Human Services applied for and received permission from the Centers for Medicare and Medicaid Services to add new members through random lottery draws from a new reservation list (Finkelstein et al., 2012). In the year following the random assignment, the treatment group had higher health care utilization, lower out-of-pocket medical expenditures and medical debt, and better self-reported physical and mental health than the control group, but it did not have detectable improvements in physical health conditions like high blood pressure (Finkelstein et al., 2012) – leaving policymakers with tough choices in balancing costs and benefits.

This research exploits Oregon's health insurance lottery selection as an instrument and contributes to two primary domains that policymakers are interested in. First, unlike numerous papers[2] that evaluate the average treatment effects, this paper contributes to estimating the heterogeneous treatment effect (or treatment heterogeneity) of lottery insurance on several outcomes like health care utilization, financial

[1] Following the June 2012 Supreme Court decision, states face a decision about whether to adopt the Medicaid expansion. However, as per the Centers for Medicare and Medicaid Services (CMS) guidance, there is no deadline for states to implement the Medicaid expansion (Kaiser Family Foundation, 2019).

[2] See: Allen et al. (2010); Baicker et al. (2013, 2017, 2014); Baicker and Finkelstein (2011); Finkelstein et al. (2012); Grossman et al. (2016); Taubman et al. (2014); Zhou et al. (2017).

strain, and self-reported physical and mental health. Exploring treatment heterogeneity helps to quantify the sizes of effects of policy intervention on different subpopulations. Along with the average treatment effects, understanding the treatment heterogeneity is valuable for policymakers to improve or reform program targeting and to surmise the underlying mechanisms that drive the results.

The second contribution of this paper is to answer how to target health insurance interventions for effective policymaking. Understanding "who should be treated" with intervention is essential for policymakers. Because, ad-hoc targeting a specific subpopulation with positive interventions can be unfair, unethical, illegal and unpolitical to some other subpopulations while intervening everyone in the population (a blanket policy) is welfare-maximizing but can be extremely costly. For example, a provision of the Affordable Care Act (ACA) was that the federal government would pay the full cost of coverage expansion through 2016 and would reimburse at least 90% of the cost of covering the newly-insured population (Norris, 2018). Oregon responded to this incentive by expanding Medicaid in January 2014 and ensured insurance to everyone with incomes up to 133% of the federal poverty line. When the federal government gradually reduced their payments, the state budget of Oregon (nearly $74 billion for 2017-2019) suffered about $1 billion budget hole mainly due to the cost of health care (Foden-Vencil, 2018).

To investigate the heterogeneous treatment effects, one can stratify the data in mutually exclusive groups or include interactions in a regression (Athey and Imbens, 2017). However, performing ad-hoc searches or $p-$hacking[3] to detect the responsive subgroups may lead to false discoveries or may mistake noise for an actual treatment effect (Davis and Heller, 2017). While with a preregistered analysis plan[4], a researcher can commit in advance to study only a subgroup, a preregistered analysis plan can help to avoid many of the issues associated with data mining or $p-$hacking. However, it may also prevent discovering unanticipated results and developing new hypotheses (Athey and Imbens, 2016). This paper implements Athey et al. (2019) "generalized random forest" methods to explore the heterogeneous treatment effects of the Oregon Health Insurance Experiment. This method re-engineers the strengths and innovations of Breiman (2001) random forest − a machine learning method − for causal inference and allow systematic investigation of the heterogeneous treatment effects that are not prone to data mining and $p-$hacking. These methods are especially useful when research includes high-dimensional covariates.

"Who should get treatment?" is a ubiquitous problem among policymakers. For example, whom to serve in youth employment programs (Davis and Heller, 2017), whom to allocate Medicare funding for hip or knee replacement surgery (Kleinberg et al., 2015), who should get job training, job search,

[3]The $p-$hacking is an exhaustive search of combinations of variables or combinations of interactions of variables or subgroups that might show statistically significant relations when, in fact, there could have no real underlying effect.

[4]Preregistered analysis plan is sets of analyses plans released in the public domain (for example The American Economic Association's registry for randomized controlled trials) by the researchers in advance prior they collect the data and learn about outcomes.

and other assistance (Kitagawa and Tetenov, 2018). This paper implements the efficient policy learning strategies of Athey and Wager (2018) to answer how to set eligibility criteria to intervene with insurance coverage. This paper design efficient policy rules considering two rationals − first, this paper constraint few observable covariates like race, gender, and residence e.t.c. Constraining specific covariates is essential for ethical, legislative, and political considerations. Second, this paper follows Kitagawa and Tetenov (2018) approach to design policy from an "intention-to-treat" perspective. This approach is crucial because the policy maker's problem is only a choice of the eligibility criteria and not the take-up rate. The take-up rate is decided by individuals. In summary, this research utilizes Oregon Health Insurance Experiment public use data and contributes to: estimate the net impact of expanding access to public health insurance; examine the sources of treatment heterogeneity on such programs and offer an optimal policy rule for such program that could maximize health related outcomes.

Section **??** summarizes the institutional background of the Oregon Health Insurance Experiment. Section **??** lays out data sources, identification strategy, and empirical methods for the cluster-robust random forest for heterogeneous estimation along with efficient policy learning strategies. Section **??** displays the results and provides discussions on findings. Section **??** concludes the study.

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