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

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Abstract

The Medicaid expansion through the Affordable Care Act (ACA) has triggered a national debate among diverse stakeholders on the impacts of insurance coverage on various dimensions of health. Randomized experiments like, the Rand Health Insurance Experiment and the Oregon Health Insurance Experiment, have generated some credible estimates of the average treatment effects. However, identical policy intervention can often distinctly affect different individuals and subpopulations. This paper exploits Oregons health insurance lottery selection to estimate the heterogeneous treatment effects of access to public health insurance on health care use, personal finance, health, and wellbeing. For this, I use the cluster-robust generalized random forest − a causal machine learning approach. I find the federal poverty line, age, household size, and numbers of uninsured months interact on several levels to exhibit heterogeneous treatment effects. Next, I use efficient policy learning strategies of Athey and Wager (2018) to propose a few practical policy rules that can maximize welfare while constraining on the ethical, legislative, and political rationals. I quantify the cost of estimated policy rules in comparison to the random assignment policy. I prescribe these policies along with worst-case effectiveness, fairness, and balance scenarios. My findings are useful for analysts, policymakers, and insurance planners to discover the underlying mechanisms that drive the health outcome results and to design or reform policy.

Keywords: Insurance, causal machine learning, heterogeneous treatment effect, efficient policy learning

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1 Introduction

This research exploits Oregon's health insurance lottery selection as an instrument and contributes to two primary domains that are relevant for policy development. First, unlike the series of papers[1] that have evaluated the average treatment effects of the Oregon Health Insurance Experiments on several outcomes, this paper contributes by estimating the heterogeneous treatment effect of lottery insurance on several issues of interest like health care use, financial strain, and self-reported physical and mental health. Second, this paper contributes possible answers regarding how to target health insurance interventions for effective policymaking. Understanding "who should be treated" with intervention is ubiquitous in policymaking. It can be unfair, unethical, and sometimes illegal to target policy to only a particular subpopulation. Moreover, intervening everybody in the population (a blanket policy) is welfare-maximizing but can be costly.[2]

As of May 13, 2019, 37 states and the District of Columbia have expanded Medicaid coverage for low-income adults to 138% of the federal poverty level through the Affordable Care Act (ACA). This provision to expand[3] the Medicaid program through the Affordable Care Act (ACA) has triggered a substantial nationwide debate among policymakers and diverse stakeholders about what effects - if any - insurance coverage has on the various dimension of health (Baicker, 2019). The findings of this paper are valuable to meet some of the issues forward by the contemporary national debate. The results of this paper can exhibit the diverse impacts on the distinct population strata on health care use, personal finance, and wellbeing regarding the expansion of public access to insurance.

There exists an extensive literature studying the impact of insurance coverage on health outcomes which report average treatment effects. A concern with this literature is that establishing causal effect 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 reveal 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.,

[1]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).

[2]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. Moreover, it 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 due to the cost of health care (Foden-Vencil, 2018).

[3]Following the June 2012 Supreme Court decision, states face a decision about whether to adopt the Medicaid expansion. But, 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).

2012), and the Oregon Health Insurance Experiment renders a unique opportunity to test 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 use, 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 − leaving policymakers with tough choices in balancing costs and benefits (Baicker, 2019).

Expensive randomized experiments like the Rand Health Insurance Experiment and the Oregon Health Insurance Experiments have generated some credible average effect estimates of expanding access to public health insurance on a population of interest. However, identical policy intervention can often distinctly affect different individuals and subpopulations in different ways. Along with average treatment effects, policymakers are usually interested in how effects of intervention vary across subpopulations. Identifying such heterogeneous treatment effects accommodate the discovery of underlying mechanisms that drive the results, which allows for more efficient design and reform of policy.

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, for large-scale investigations of effect heterogeneity, standard $p-$values of standard (single) hypothesis tests are no longer valid because of the multiple hypothesis testing[4] problems (Lan et al., 2016; List et al., 2019). Moreover, performing ad-hoc searches or $p-$hacking[5] to detect the responsive subgroups may lead to false discoveries or may mistake noise for an actual treatment effect (Davis and Heller, 2017). To avoid many of the issues associated with data mining or $p-$hacking, researchers can commit in advance to study only a subgroup by a preregistered analysis plan.[6] However, it may also prevent discovering unanticipated results and developing new hypotheses (Athey and Imbens, 2016).

This paper implements the Athey et al. (2019) cluster-robust version of the 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 predictive

[4]The "multiple hypothesis testing problems" leads to the so-called "ex-post selection problem," which is widely recognized in the program evaluation literature. For example, for fifty single hypotheses tests, the probability that at least one test falsely rejects the null hypotheses at the 5% significance level (assuming independent test statistics as an extreme case) is $1 - 0.95^{50} = 0.92$ or 92%.

[5]The $p-$hacking is an exhaustive search for statistically significant relations from combinations of variables or combinations of interactions of variables or subgroups. The $p-$hacking could lead to discovering the statistically significant relationship, when, in fact, there could have no real underlying effect.

[6]A preregistered analysis plan is sets of analyses plans released in the public domain by the researchers in advance prior they collect the data and learn about outcomes. For example, The American Economic Association's registry for randomized controlled trials is a reputable platform for conducting a preregistered analysis plan.

machine learning method − for causal inference. These modifications allow systematic investigation of the heterogeneous treatment effects that are not prone to data mining and $p-$hacking. Moreover, these methods are especially useful when research includes high-dimensional covariates. In this paper, I show the causal thresholds for distinct subpopulations where the impacts of Medicaid intensify and subdue. These realms have not been explored earlier and are some unique contributions to the literature. I scrutinize these separate subgroup for 36 different outcomes of interest. These outcomes are extensive and intensive margins of health care use, preventive care use, financial strain, mental and physical wellbeing and mechanisms of care, quality, and satisfaction of health care service usages.

"Who should get treatment?" is a widespread issue in policy design. 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, 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 implements the efficient policy learning strategies of Athey and Wager (2018) to answer questions of how to set eligibility criteria to intervene with insurance coverage. This paper designs efficient policy rules considering two rationales − 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. Individuals decide the take-up rate. I put forward various policies for each outcome of interest along with the cost of each of the policy compared with the random assignment policy. To model some worst-case scenarios of the purpose policies, I also develop lower-bounds for policy effectiveness, fairness, and balance.

In summary, this research uses Oregon Health Insurance Experiment public-use data and contributes to estimating the net impact of expanding access to public health insurance; examining the sources of treatment heterogeneity on such programs and offering an optimal policy rule for such program that could maximize health-related outcomes. The findings of this paper are useful for analysts, policymakers, and insurance designers to discover the underlying mechanisms that drive the health outcome results and to design or reform policy.

Section **??** summarizes the institutional background of the Oregon Health Insurance Experiment. Section **??** summarizes approaches to study health insurance and health outcomes and explains how causal machine learning can help to analyze different research questions. Section **??** lays out 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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