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

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**Abstract**

The Medicaid expansion through the Affordable Care Act (ACA) has triggered the national debate among diverse stakeholders regarding the impacts of insurance coverage on various dimensions of health. Expensive randomized experiments like the Rand Health Insurance Experiment and the Oregon Health Insurance Experiments have generated some credible estimates of the average treatment effects. However, identical policy intervention can often distinctly affects 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 utilization, personal finance, health, and wellbeing. For this, I implement the generalized random forest − a causal machine learning − approach of (Athey et al., 2019). I find the federal poverty line and age are essential variables, and their interactions on several levels explain the heterogeneous treatment effects. Next, I utilize efficient policy learning strategies of Athey and Wager (2018) to propose a few practical policy rules that can maximize the overall welfare while constraining on the ethical, legislative, and political reasons. My findings 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.

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

**JEL Classification:**

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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[1] 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.

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 affects individuals and subpopulations. Along with average treatment effects, policymakers are usually interested in how effects of intervention vary across subpopulations. Identifying such "heterogeneous treatment effect" accommodates to discover the underlying mechanisms that drive the results and to design or reform policy.

This research exploits Oregon's health insurance lottery selection as an instrument and contributes to two primary domains that intrigue policymakers. First, unlike series of papers[2] that have evaluated the average treatment effects of the Oregon Health Insurance Experiments on several outcomes, this paper provides the heterogeneous treatment effect of lottery insurance on several issues of interest like health care utilization, financial strain, and self-reported physical and mental health. Second, this paper contribution to answer how to target health insurance interventions for effective policymaking. Understanding "who should be treated" with intervention is ubiquitous in policymaking. Because, it can be unfair, unethical, and illegal to policy target exclusively to a particular subpopulation. Moreover, intervening everyone in the population (a blanket policy) is welfare-maximizing but can be extremely costly[3].

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[4] to detect the responsive subgroups may lead to false discoveries or may mistake

[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).

[3]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 mainly due to the cost of health care (Foden-Vencil, 2018).

[4]The $p-$hacking is an exhaustive search for statistically significant relations from combinations of variables or com-

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 pre-registered analysis plan[5]. 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. 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.

"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, 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. Individuals decide the take-up rate. 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.

binations 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.

[5]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.

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