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

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Abstract

As of May 13, 2019, 37 states and the District of Columbia expanded Medicaid through the Affordable Care Act (ACA) for the low-income adults to 138% of the federal poverty line. Following the June 2012 Supreme Court decision, several states face a decision about whether to adopt the Medicaid expansion. This situation has triggered a substantial national debate among diverse stakeholders regarding the impact of expanding access to public health insurance on various dimensions of health care utilization, personal finance, health, and wellbeing. Expensive randomized experiments like the Rand Health Insurance Experiment and the Oregon Health Insurance Experiments have generated some credibly estimates of the average effect of expanding access to public health insurance on a population of interest. However, identical policy intervention often distinctly affects individuals and subpopulations. Along with average treatment effects, policymakers are usually interested in how effects vary across subpopulations. Understanding such heterogeneous treatment effect helps to learn the underlying mechanisms that drive the results and to design or reform policy. I utilize the Oregon health insurance experiment public use data to estimate heterogeneous treatment effects of insurance on health and personal financial outcomes. Then, I propose insurance assignment strategies constraining for ethical, legislative, and political reasons that can maximize the overall welfare. I find the federal poverty line and age interact on several levels to trigger heterogeneous treatment effects.

Keywords: Insurance, causal inference, machine learning

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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" (Baicker, 2019).

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 (Baicker, 2019).

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 from 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) that have evaluated the average treatment effects of the Oregon Health Insurance Experiments on several outcomes, this paper provides the heterogeneous

[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).

treatment effect of lottery insurance on several issues of interest like health care utilization, financial strain, and self-reported physical and mental health. Identical policy intervention often distinctly affects individuals and subpopulations. Therefore, exploring the effects of policy intervention on different subpopulations 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. 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. 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).

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 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[2], researchers can commit in advance to study only a subgroup by a pre-registered analysis plan[3]. 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

[2]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.

[3]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.

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.

References

Allen, H., Baicker, K., Finkelstein, A., Taubman, S., and Wright, B. J. (2010). What the Oregon Health Study can Tell us about Expanding Medicaid. *Health Affairs*, 29(8):1498–1506.

Athey, S. and Imbens, G. (2016). Recursive partitioning for heterogeneous causal effects. *Proceedings of the National Academy of Sciences*, 113(27):7353–7360.

Athey, S. and Imbens, G. (2017). Chapter 3 - the econometrics of randomized experiments. In Banerjee, A. V. and Duflo, E., editors, *Handbook of Field Experiments*, volume 1 of *Handbook of Economic Field Experiments*, pages 73 – 140. North-Holland.

Athey, S., Tibshirani, J., Wager, S., et al. (2019). Generalized random forests. *The Annals of Statistics*, 47(2):1148–1178.

Athey, S. and Wager, S. (2018). Efficient Policy Learning. pages 1–37.

Baicker, K. (2019). The effect of health insurance on spending, health, and well-being – evidence and implications for reform.

Baicker, K., Allen, H. L., Wright, B. J., and Finkelstein, A. N. (2017). The Effect Of Medicaid On Medication Use Among Poor Adults: Evidence from Oregon. *Health Affairs*, 36(12):2110–2114.

Baicker, K. and Finkelstein, A. (2011). The Effects of Medicaid Coverage Learning from the Oregon Experiment. *New England Journal of Medicine*, 365(8):683–685.

Baicker, K., Finkelstein, A., Song, J., and Taubman, S. (2014). The Impact of Medicaid on Labor Market Activity and Program Participation: Evidence from the Oregon Health Insurance Experiment. *American Economic Review*, 104(5):322–328.

Baicker, K., Taubman, S. L., Allen, H. L., Bernstein, M., Gruber, J. H., Newhouse, J. P., Schneider, E. C., Wright, B. J., Zaslavsky, A. M., and Finkelstein, A. N. (2013). The Oregon Experiment Effects of Medicaid on Clinical Outcomes. *New England Journal of Medicine*, 368(18):1713–1722.

Breiman, L. (2001). Random forests. *Machine Learning*, 45(1):5–32.

Davis, J. M. and Heller, S. B. (2017). Using Causal Forests to Predict Treatment Heterogeneity: An application to Summer Jobs. *American Economic Review*, 107(5):546–550.

Finkelstein, A., Taubman, S., Wright, B., Bernstein, M., Gruber, J., Newhouse, J. P., Allen, H. L., Baicker, K., and Oregon Health Study Group, . (2012). The Oregon Health Insurance Experiment: Evidence From The First Year. *Quarterly Journal of Economics*, 127(August (3)):1057–1106.

Foden-Vencil, K. (2018). Oregon Measure 101: What You Need To Know . News — OPB.

Grossman, R. L., Heath, A. P., Ferretti, V., Varmus, H. E., Lowy, D. R., Kibbe, W. A., and Staudt, L. M. (2016). Effect of Medicaid Coverage on ED Use Further Evidence from Oregon's Experiment. *New England Journal of Medicine*, 363(1):1–3.

Kaiser Family Foundation (2019). Status of state action on the medicaid expansion decision.

Kitagawa, T. and Tetenov, A. (2018). Who Should Be Treated? Empirical Welfare Maximization Methods for Treatment Choice. *Econometrica*.

Kleinberg, J., Ludwig, J., Mullainathan, S., and Obermeyer, Z. (2015). Prediction Policy Problems. *American Economic Review*.

Levy, H. and Meltzer, D. (2008). The Impact of Health Insurance on Health. *Annual Review of Public Health*, 29(1):399–409.

Norris, L. (2018). Oregon and the ACA's Medicaid expansion: eligibility, enrollment and benefits — healthinsurance.org.

Taubman, S. L., Allen, H. L., Wright, B. J., and Baicker, K. (2014). Oregon's Health Insurance Experiment. *Science*, 343(6168):263–268.

Zhou, R. A., Baicker, K., Taubman, S., and Finkelstein, A. N. (2017). The uninsured do not use the emergency department more- they use other care less. *Health Affairs*, 36(12):2115–2122.