Effect of Health Insurance Coverage on Health & Financial Outcomes

ECMA 31350 Final Presentation

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Introduction

Motivation

Economic theory offers ambiguous predictions for the impact of expanding health insurance on outcomes such as

- health-care use,
- economic well-being, and
- long-term health outcomes.

It is difficult to separate the effects of insurance from confounding factors such as income and initial health in observational studies.

The **Oregon Health Insurance Experiment (2008-2010)** provides for a great opportunity to investigate this through a randomized controlled design.

Setting and Background

- In 2008, Oregon implemented a limited expansion of its Medicaid program for low-income adults through a lottery, selecting names from a waiting list to fill a limited number of available spots. Those selected had the opportunity to apply for Medicaid and to enroll if they met eligibility requirements.
- The lottery can be used to assess both the effects of lottery selection and the effects of Medicaid coverage itself on a range of outcomes.
- For this project, we decided to study the affect of **health insurance coverage** itself, upon some **outcomes related to health and financial well-being**.

Research Gap → Need for ML → Our Approach

1. ML in health insurance literature is usually used for prediction, and in an experimental context, we could only find a few (very recent) papers on the application of ML for causal investigation. It will be interesting to continue building this literature.
2. Additionally, we have 5+ potential covariates implying that classic non-parametric methods no longer satisfy our needs, which pushes for modern ML methods.

In this project, we:

- Investigate the conditional local ATE using instrumental/causal forest;
- Then calculate the local ATE, in general, using DML while taking into account missing values from follow-up surveys through imputation.

Literature Review

Literature Review

1. Finkelstein et al. (2012)
   - Used the 12-month mail survey data and some other administrative data (not publicly available) to estimate LATE associated with Medicaid using 2SLS.
2. Hattab et al. (2024)
   - Used the in-person survey data to estimate CATE using instrumental forest. Found weak heterogeneity in effect across subgroups based on gender, age, and race.
3. Goto et al. (2024)
   - Used the in-person survey data and causal forest approach to detect heterogeneous effects of Medicaid coverage on depression. Found reduced the risk of depression and greater impacts for populations at-risk at baseline.

Data

Data

- The Oregon Health Insurance Experiment (OHIE) is a randomized controlled trial (RCT) that started in 2008, with survey follow-ups until 2010.
- It contains information on all the 74,922 individuals who enrolled in the lottery.
- We use the the 12-month-mail survey post enrollment due to it having more observations as well as relevant follow up variables for our outcomes.
- We also consider self-reported variables for demographic information, enrollment status in government programs, and health status and insurance needs, for follow-up participants.

Method and Analysis

Method I: Motivating Causal Forest DML

Gradient Boosting

Given the high-dimmensional data, we used gradient boosting via XGBoost to identify the most important features.

- Reduce dimension of data $\rightarrow$ computationally efficient analysis.
- We selected features based on a F-score threshold of 300.

Implementation Approach

Balance, HTE, NAs and Imputation

- The covariates chosen are not perfectly balanced.
- There are heterogenous effects.
- Imputed data using K-NN : Had little effect on characteristics of the data

Next: We can further provide sample weights, using propensity scores, in the CausalForestDML approach.

Method I: Causal Forest DML Model

First stage:

- Random Forest Classifier to model treatment, and Random Forest Regressor for the outcomes (cross-fitting).

Second stage:

- The treatment effects are estimated using the residuals obtained from the first stage.

Solves

$$E[(Y - E|X] - \langle\theta(x), T - E[T|X]\rangle - \beta(x))(T; 1)|X = x] = 0$$

We used heterogeneity score as the criterion which finds splits that maximize the pure parameter heterogeneity score.

Method I: Results Imputed Data

Variable	ATE	SE	p-value	Significant
happiness	-0.05143	0.00424	5.88E-11	TRUE
health (overall)	-0.00624	0.00310	0.05721	FALSE
health (change)	-0.02023	0.00255	9.54E-08	TRUE
bad days (physical)	0.79423	0.07458	6.37E-10	TRUE
bad days (mental)	0.44775	0.08063	1.64E-05	TRUE
limits ability to work	0.09005	0.00302	0	TRUE
disinterest	0.05536	0.00666	4.43E-08	TRUE
felt sad/depressed	0.04394	0.00617	5.04E-07	TRUE
any OOP health costs	-0.09862	0.00321	0	TRUE
total OOP health costs	-2656.39	453.36	8.14E-06	TRUE
owe for medical expenses	-0.05911	0.00296	3.77E-15	TRUE
borrowed for medical expenses	-0.09182	0.00279	0	TRUE
refused care due to money	-0.02025	0.00194	9.32E-10	TRUE
on medication	0.08994	0.00246	0	TRUE
number of meds	0.56342	0.01726	0	TRUE
primary care visits	0.19769	0.00298	0	TRUE
number of visits (PHC)	1.16298	0.02110	0	TRUE
any ER visits	0.06134	0.00279	4.44E-16	TRUE
number of visits (ER)	0.16585	0.00800	1.78E-15	TRUE
any hospital visits	0.06183	0.00250	0	TRUE
number of visits (hosp)	0.10667	0.00527	3.11E-15	TRUE

Method II: Motivating DML Approach for LATE with NA

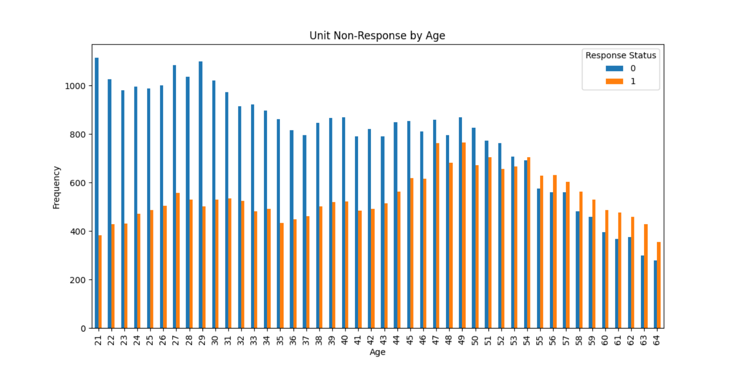
Quote from Finkelstein et al. (2012):

"The survey data [...] with a 50% effective response rate, are subject to potential nonresponse bias [...] These outcomes are only available for individuals who responded to the mail survey and may therefore not be representative of the full sample."

Problem: This is concerning because we do not have non-response at random!

- item non-response (controlled by K-NN imputation)
- unit non-response

Method II: Motivating DML Approach for LATE with NA



- Observed similar imbalances for gender, protocol intensity, access to phone, existing governmental programs, etc., all of which affect Y!

Question: Can we address this non-response bias in estimating LATE using machine learning?

Method II: Theorem

Set-up: Let

- Y - outcome (health & financial outcomes),
- D - treatment (insurance coverage),
- Z - instrument (lottery selection),
- W - covariates such that Z is a valid instrument,
- S - responder status,
- X - covariates such that missing at random, i.e. $(Y, D, Z, W) \perp S \mid X$, is plausible.

Then this score function is Neyman orthogonal:

$$g(A; \tau_{LATE}, \eta) = (g^{1,1;o}(A;\eta) - g^{1,0;o}(A;\eta)) - (g^{2,1;o}(A;\eta) - g^{1,1;o}(A;\eta))\tau_{LATE},$$

Method II: Theorem

where:

$$
\begin{aligned}
g^{1,1;o}(A; r, q, a_1, b_1) &= \frac{YZS}{rq} - (Z - r) \cdot \frac{a_1}{r^2} - (S - q) \cdot \frac{b_1}{rq}, \\
g^{1,0;o}(A; r, q, a_0, b_0) &= \frac{Y(1 - Z)S}{(1 - r)q} - (Z - r) \cdot \frac{a_0}{(1 - r)^2} \\
&\quad - (S - q) \cdot \frac{b_0}{(1 - r)q}, \\
g^{2,1;o}(A; r, q, f_1, g_1) &= \frac{Y(1 - Z)S}{rq} - (Z - r) \cdot \frac{f_1}{r^2} - (S - q) \cdot \frac{g_1}{rq}, \\
g^{2,0;o}(A; r, q, f_0, g_0) &= \frac{Y(1 - Z)S}{(1 - r)q} - (Z - r) \cdot \frac{f_0}{(1 - r)^2} \\
&\quad - (S - q) \cdot \frac{b_0}{(1 - r)q},
\end{aligned}
$$

Method II: Theorem

and the nuisance parameters $\eta = (r, q, a_1, a_0, b_1, b_0, f_1, f_0, g_1, g_0)$ are:

$$
\begin{aligned}
r(W) &= \mathbb{E}[Z \mid W] = \mathbb{P}[Z = 1 \mid W], \\
q(X) &= \mathbb{E}[S \mid X] = \mathbb{P}[S = 1 \mid X] = \mathbb{P}[S = 1 \mid W, X] = q(X, W), \\
a_1(W) &= \mathbb{E}[YZ \mid S = 1, W], \quad a_0(W) = \mathbb{E}[Y(1 - Z) \mid S = 1, W], \\
b_1(X, W) &= \mathbb{E}[YZ \mid S = 1, X, W], \quad b_0(X, W) = \mathbb{E}[Y(1 - Z) \mid S = 1, X, W], \\
f_1(W) &= \mathbb{E}[DZ \mid S = 1, W], \quad f_0(W) = \mathbb{E}[D(1 - Z) \mid S = 1, W], \\
g_1(X, W) &= \mathbb{E}[DZ \mid S = 1, X, W], \quad g_0(X, W) = \mathbb{E}[D(1 - Z) \mid S = 1, X, W].
\end{aligned}
$$

Method II: Results

	(1)	(2)	(3)	(4)	(5)	(6)
	Healthcare Utilization					
prescription drugs	0.088	-0.119	-0.121	0.347	-0.425	-0.436
outpatient visits	0.212	0.079	0.077	1.083	0.510	0.491
ER visits	0.022	-0.084	-0.084	0.026	-0.163	-0.165
hospital visits	0.008	-0.014	-0.015	0.021	-0.004	-0.004
	Financial Strain					
OOP medical expense	-0.200	-0.328	-0.332			
owe medical expense	-0.180	-0.390	-0.391			
borrowed money for medical expense	-0.154	-0.260	-0.263			
refused treatment due to money	-0.036	-0.070	-0.070			
	Health					
unhappiness	-0.191	-0.643	-0.649			
health (overall)	-0.133	-0.273	-0.278			
health (change)	-0.113	-0.208	-0.210			
bad days (physical)	-1.317	-4.563	-4.624			
bad days (mental)	-2.082	-5.464	-5.554			
limits ability to work	-1.585	-0.210	-0.213			

Columns (1)-(3) for extensive margin (any), (4)-(6) for total utilization. Columns (1) & (4) correspond to Finkelstein et al. (2012) LATE estimates, (2) & (5) correspond to the propensity score $p(X)$, (3) & (6) correspond to the propensity score $p(X, W)$.

Key Takeaways

For **Method I: CausalForestDML** with imputed values:

- Results are significant, effects align with previous analyses though diminished, however – hyperparameter tuning required to check for robustness and interpretability of effects

For **Method II: LATE with missing values**:

- columns (2) & (3) and (5) & (6) are similar $\implies$ some evidence that the independence assumption holds
- compared to Finkelstein et al. (2012):
  - our LATE estimates are diminished or even opposite in sign compared to estimates for healthcare utilization
  - but report greater reduction on financial strain and negative self-perceived health outcomes
  - formal interpretation will have to wait after obtaining SE

Robustness Checks/Next Steps

1. Checking for treatment and control balance at the baseline
2. Using simple propensity score matching + sample weights from survey to check for covariate balance in Method I
3. For DML for missing values:
   - Generate bootstrap standard errors
   - Ensuring item non-response imputation works properly
   - Use the alternative treatment variable used in Finkelstein et al. (2012) to see how well it aligns with current analysis as well as past results
4. Checking for/comparing results for other outcome variables corresponding to each treatment (lottery vs coverage)
5. Checking for/comparing results for 25-month survey responses

Appendix

Method I: Results Drop NA

Variable	ATE	SE	p-value	Significant
happiness_12m	-0.05143	0.00424	5.88E-11	TRUE
health_gen_bin_12m	-0.00624	0.00310	0.05721	FALSE
health_chg_bin_12m	-0.02023	0.00255	9.54E-08	TRUE
baddays_phys_12m	0.79423	0.07458	6.37E-10	TRUE
baddays_ment_12m	0.44775	0.08063	1.64E-05	TRUE
health_work_12m	0.09005	0.00302	0	TRUE
dep_interest_12m	0.05536	0.00666	4.43E-08	TRUE
dep_sad_12m	0.04394	0.00617	5.04E-07	TRUE
cost_any_oop_12m	-0.09862	0.00321	0	TRUE
cost_tot_oop_12m	-2656.39	453.36	8.14E-06	TRUE
cost_any_owe_12m	-0.05911	0.00296	3.77E-15	TRUE
cost_tot_owe_12m	2630427262	385992093.3	9.73E-07	TRUE
cost_borrow_12m	-0.09182	0.00279	0	TRUE
cost_refused_12m	-0.02025	0.00194	9.32E-10	TRUE
rx_any_12m	0.08994	0.00246	0	TRUE
rx_num_mod_12m	0.56342	0.01726	0	TRUE
doc_any_12m	0.19769	0.00298	0	TRUE
doc_num_mod_12m	1.16298	0.02110	0	TRUE
er_any_12m	0.06134	0.00279	4.44E-16	TRUE
er_num_mod_12m	0.16585	0.00800	1.78E-15	TRUE
hosp_any_12m	0.06183	0.00250	0	TRUE
hosp_num_mod_12m	0.10667	0.00527	3.11E-15	TRUE