Study data

The US state of Oregon's Medicaid program provides health insurance cover for low-income, uninsured, non-disabled adults who were ineligible for other public health insurance. Those enrolled with the Medicaid program paid US$0-20 each month for this coverage. In 2004, the program was closed to new enrollees because of budgetary limits.

In 2008 Medicaid coverage for low-income adults in Oregon was expanded based on a lottery. Eligible adults were randomly selected to be given the option to apply for Medicaid coverage or placed on a waiting list and a baseline survey conducted (for more details see e.g. Baiker *et al*., 2013). The lottery was stratified by the size of the household with a constant randomisation ratio across strata. In this assignment we will consider data from n=10,758 study participants who were surveyed at baseline and responded (5483 were selected to be able to apply for Medicaid, 5275 were not selected, variable **`Medicaid_option`** below).

Not everyone who was given the option to apply for Medicaid was also enrolled for Medicaid coverage. To enrol individuals had to fill out an application that demonstrated their eligibility within 45 days of winning the lottery. A measure of successful Medicaid enrollment is given by the variable **`Medicaid_cover`** below. In our dataset only 1760 of the 5483 participants who were selected in the lottery (32%) were also enrolled for Medicaid coverage. Many factors might influence whether a low-income adult successfully applies for this insurance cover - some observed and some unobserved.

Clinical and health care system use outcomes were assessed by another survey approximately 1 year after the lottery. We provide a detailed list of variables below.

The dataset **`Oregon.dta`** is a subset of the original data (https://doi.org/10.7910/DVN/SJG1ED) and contains the following variables:

Experimental design:

- **`Number_house:`** estimated size of household
- **`Medicaid_option:`** able to apply for Medicaid (1=selected in lottery, 0=not selected in lottery)
- **`Medicaid_cover:`** enrolment for Medicaid coverage (1=selected in lottery and enrolled (application received within deadline and approved), 0=selected in lottery but not enrolled), note that this variable is set to missing for all those who were not selected in the lottery and for some participants who were selected but the application information was not recorded

Baseline survey:

General health:

- **`bmi_inp:`** body mass index
- **`chl_inp:`** total cholesterol (mg/dL)
- **`bp_sar_inp:`** systolic blood pressure (mmHg)
- **`bp_dar_inp:`** diastolic blood pressure (mmHg)
- **`phqtot_inp:`** PHQ-9 total severity score (higher score indicates more severe depression)
- **`cvd_risk_point_inp:`** cardiovascular risk score (Framingham risk score, higher score indicates higher risk)

Existing diagnoses:

- **ast_dx_pre_lottery_inp:** asthma diagnosis (1=yes, 0=no)
- **dia_dx_pre_lottery_inp:** diabetes diagnosis (1=yes, 0=no)
- **hbp_dx_pre_lottery_inp:** high blood pressure diagnosis (1=yes, 0=no)
- **chl_dx_pre_lottery_inp:** high cholesterol diagnosis (1=yes, 0=no)
- **ami_dx_pre_lottery_inp:** heart attack diagnosis (1=yes, 0=no)
- **emp_dx_pre_lottery_inp:** chronic obstructive pulmonary disease (COPD) diagnosis (1=yes, 0=no)
- **kid_dx_pre_lottery_inp:** kidney failure diagnosis (1=yes, 0=no)
- **cancer_dx_pre_lottery_inp:** cancer diagnosis (1=yes, 0=no)
- **dep_dx_pre_lottery_inp:** depression diagnosis (1=yes, 0=no)

Health care finance:

- **ins_any_inp:** any existing medical insurance (1=yes, 0=no)
- **owe_inp**: currently owing money for health expenditure (1=yes, 0=no)
- **catastrophic_exp_inp:** previously incurred catastrophic health expenditure (1=yes, 0=no)

1-year survey:

General health:

- **health_change_bin:** change in health (1=better, 0=same or worse)
- **pcs8_score_inp:** SF-8 physical health component score (higher score indicates better health)
- **mcss8_score_in:** SF-8 mental health component score (higher score indicates better health)

New diagnoses:

- **dia_dx_post_lottery_inp:** diabetes diagnosis (1=yes, 0=no)
- **hbp_dx_post_lottery_inp:** high blood pressure diagnosis (1=yes, 0=no)
- **chl_dx_post_lottery_inp:** high cholesterol diagnosis (1=yes, 0=no)
- **dep_dx_post_lottery_inp:** depression diagnosis (1=yes, 0=no)

The Oregon experiment was a landmark study providing an opportunity to evaluate the effectiveness of providing low income adults with the option to apply for Medicaid coverage and also the efficacy of having Medicaid coverage.

I estimated the causal effect of the ability to apply for Medicaid on the 7-year outcomes, which include general health and new diagnoses, for the entire population. Specifically, I defined the estimands for each variable type, using mean difference effect sizes and

population averages. I used Y o denote any outcome variable and R to denote the ability to apply for Medicaid (lottery selection).

We are targeting an ITT/ACE (causal effect of treatment offer) estimate for each of our outcome variable. Since there is non-adherence with the treatment offers (i.e., applying for Medicaid != enrolling in Medicaid), we can only estimate treatment effectiveness by ITT analysis.

We have continuous and binary outcome variables in the dataset.
For continuous outcome variables, we define ITT estimand:

ACE = E[(Y(R=1) - Y(R=0))]

Here we are calculating the mean differences in the population as an effect size. For binary outcomes, we can consider the Causal risk difference:

RD: E[Y(1)] − E[Y(0)] = Prob[Y(R=1)=1] –Prob[Y(R=0)=1]

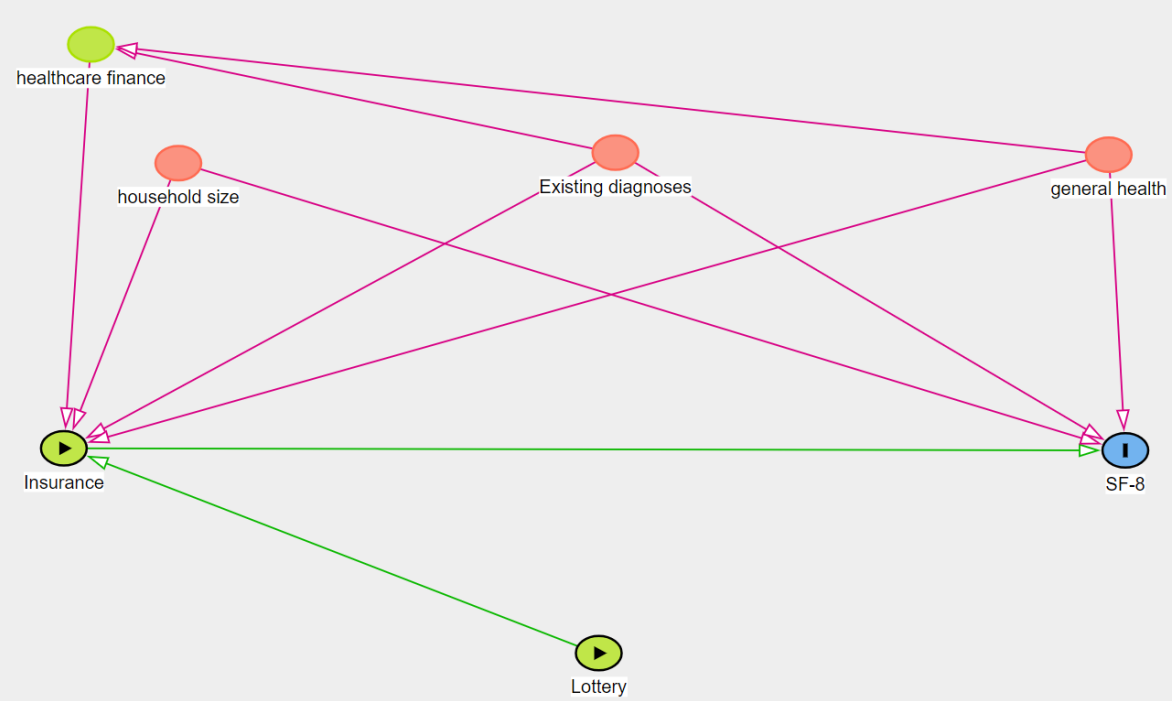
Now, I suggest an estimator for each of my estimands and explain why I am using it:

We are implementing the ITT analysis as our estimator. We will include all participants as originally assigned to their original group, regardless of whether they complied to the treatment protocol. For continuous outcomes, one can estimate the effect of lottery selection by fitting ordinary least squares regressions and comparing the average outcome for all individuals selected in the lottery to the average outcome for all control individuals. Similarly, we implement linear regression to estimate effect of lottery selection for binary outcomes. We also implemented the average marginal effects using logistic regression and tried comparing this estimate with the bootstrap from linear regression on binary outcome. There's a maximum difference of 0.002 in all our observed coefficients. This double checking helped clarify whether doing linear regression on binary followed by bootstrapping is a valid approach. Given above information on study design, since randomisation was conducted after stratifying by household size, we can safely assume that this variable does not predict lottery selection outcomes hence need not be adjusted to prevent confounding bias. However, household size predicts post-lottery outcomes, therefore, we include it in the regression equation to improve precision.

Following are the causal effect estimates:

Outcome variable	Effect size measure	Causal effect estimate	95% CI
Change in health	ITT (logit)	.0039	*
	ITT (OLS with bootstrapping)	.0036	-.0157 .0229
SF-8 physical health	ITT (OLS)	.2081	-.197 .6132
SF-8 mental health	ITT (OLS)	.0347	-.3026 .372
New diabetes diagnosis	ITT (logit)	.0091	*
	ITT (OLS with bootstrapping)	.0081	.0024 .0138
New high blood pressure diagnosis	ITT (logit)	.0047763	*
	ITT (OLS with bootstrapping)	.0027235	-.0083 .0137
New high cholesterol diagnosis	ITT (logit)	.0024	*
	ITT (OLS with bootstrapping)	.0016	-.0103 .0135
New depression diagnosis	ITT (logit)	.0082	*
	ITT (OLS with bootstrapping)	.006	-.0037 .0157

Used DAGitty to draw a DAG for the causal effect of having Medicaid (=being enrolled for) coverage on an SF-8 outcome at year



- Lottery and SF-8 do not share any unobserved common causes
- Lottery does not cause SF-8 other that by affecting Insurance
- SF-8 does not cause Lottery
- There is no collider path connecting Lottery with SF-8

I estimated the causal effect of being enrolled in Medicaid on the two SF-8 outcomes (physical health component score and mental health component score) for the entire population using inverse probability of treatment weighting (IPTW). Specifically, I checked the balance of baseline variables across enrolment groups. I assessed the balance in variable categories such as stratifier, general health variables, existing diagnoses, and health care finance using Stata output. Standardized differences with |d|<0.1 were considered balanced. I identified the variables that were found to be unbalanced. I recoded the Medicaid_cover variable to account for the fact that those not selected by the lottery could not enrol in Medicaid.

	Mean in treated	Mean in Untreated	Standardised diff.
number_house	1.12	1.14	-0.063
dep_dx_pos~p	0.06	0.05	0.031
bmi_inp	30.32	30.23	0.011
chl_inp	207.92	207.47	0.013

bp_sar_inp	121.74	121.28	0.027
bp_dar_inp	78.08	77.49	0.048
phqtot_inp	7.66	7.31	0.056
cvd_risk_p~p	0.09	0.08	0.114
ast_dx_pre~p	0.20	0.18	0.049
dia_dx_pre~p	0.08	0.09	-0.042
hbp_dx_pre~p	0.24	0.22	0.045
chl_dx_pre~p	0.16	0.16	0.012
ami_dx_pre~p	0.03	0.02	0.066
emp_dx_pre~p	0.04	0.03	0.097
kid_dx_pre~p	0.02	0.02	-0.005
cancer_dx_~p	0.06	0.05	0.011
dep_dx_pre~p	0.41	0.37	0.068
ins_any_inp	0.66	0.38	0.572
owe_inp	0.51	0.58	-0.154
catastroph~p	0.04	0.05	-0.053

-Cardiovascular risk scores, any existing medical insurance and currently owing money for health expenditure were imbalanced variables

I constructed inverse probability of treatment weights (IPTW) from a logistic regression on all 19 baseline variables. Below is the Stata output describing the balance of observed confounders in the pseudo-samples, categorized by stratifier, general health variables, existing diagnoses, and health care finance:

	Mean in treated	Mean in Untreated	Standardised diff.
number_house	1.15	1.14	0.028
dep_dx_pos~p	0.05	0.05	-0.011
bmi_inp	30.22	30.23	-0.002
chl_inp	207.33	207.61	-0.008
bp_sar_inp	120.87	121.35	-0.027
bp_dar_inp	77.27	77.59	-0.026
phqtot_inp	7.27	7.37	-0.015
cvd_risk_p~p	0.08	0.08	-0.037
ast_dx_pre~p	0.19	0.19	-0.003
dia_dx_pre~p	0.09	0.09	0.009
hbp_dx_pre~p	0.23	0.22	0.006
chl_dx_pre~p	0.17	0.16	0.017
ami_dx_pre~p	0.02	0.02	-0.012
emp_dx_pre~p	0.03	0.03	0.011
kid_dx_pre~p	0.02	0.02	0.016
cancer_dx_~p	0.05	0.05	-0.011
dep_dx_pre~p	0.38	0.38	0.009
ins_any_inp	0.42	0.43	-0.027
owe_inp	0.60	0.57	0.051
catastroph~p	0.05	0.05	0.015

Once balance was confirmed as adequate, I proceeded with the following steps:

Estimated the Average Treatment Effects (ATE) using IPTW:

Using the IPTW without stabilization, I estimated the ATE for the two SF-8 outcomes.

Re-estimated ATE by Adjusting for Covariates in the Outcome Model:

Instead of weighting, I adjusted for the same covariates directly in the outcome model.

Re-estimate ATE using an Augmented Estimator

Estimator	$\widehat{\mathbf{ATE}}$	**95% CI**	**Assumptions**
Naïve estimator (no adjustment): -SF-8 physical health score -SF-8 mental health score	 -1.572 -0.257	 [-2.108, -1.036] [-0.840, 0.324]	No observed or unobserved confounding
iii. IPTW estimator: -SF-8 physical health score -SF-8 mental health score	 -.796 .017	 [-1.386, -.206] [-.457 , .492]	1. No interference 2. Consistency 3. No unobserved confounding (conditional independence) 4. Correct specification of the pscore model • 5. Positivity
iv. Regression adjustment estimator: -SF-8 physical health score -SF-8 mental health score	 -.805 -.001	 [-1.397 , -.213] [-.476 , .474]	No unobserved confounding, linear relationship between outcome and covariates, normality of error term
v. Augmented estimator (doubly robust): -SF-8 physical health score -SF-8 mental health score	 -.832 .011	 [-1.421, -.242] [-.461, .483]	Positivity , no unobserved confounding

Now estimating the CACE:

Estimator	$\widehat{\mathbf{CACE}}$	**95% CI**
i. Minimally adjusted IV estimator -SF-8 physical health score -SF-8 mental health score	1.306 2.23	[-.126 , 2.738] [.685 , 3.775]
ii. Fully adjusted IV estimator		

-SF-8 physical health score	.599	[-.684 , 1.88]
-SF-8 mental health score	.167	[-.901, 1.235]

Assumptions made for CACE:

1. No unmodelled common causes of our instrument 'applying for Medicaid' and our outcome (SF-8 scores after 1 year). This is fulfilled due to design of the study as application process is randomised.
2. Exclusion restriction: for non-compliers, the offer of applying for Medicaid in itself does not influence the outcome SF-8. The instrument variable should affect the outcome only through our treatment, i.e., enrolling in Medicaid. This cannot be checked empirically.
3. Relevance: the offer to apply for Medicaid increases likelihood of enrolment in Medicaid. This can be checked empirically by comparing proportions enrolling in Medicaid when offered to apply vs not offer to apply.
4. Monotonicity : There are no defiers, that is there are no participants in the target population who would enrol in Medicaid if they were not offered to apply, and who would not enrol if it were offered to apply. This is fulfilled due to study design that does not give the option to enrol in the study if you were not offered to apply for Medicaid in the first place.

Interpreting our findings for the following results:

- estimator of the causal effect of the ability to apply for Medicaid coverage
- augmented estimator of the causal effect of having Medicaid coverage
- minimally adjusted IV estimator of the causal effect of having Medicaid coverage

- The ITT estimate estimates the effectiveness of the offer to apply for insurance instead of the effect of insurance enrolment. It includes all participants as originally assigned to their groups (random allocation of ability to apply Medicaid vs not) regardless of whether they complied to this randomised protocol. Since there was non-compliance with the randomly allocated insurance offer, ITT no longer assesses efficacy. Therefore, our estimates of .208 and .0347 are that of the effectiveness of ability to apply for Medicaid coverage

-We would expect out efficacy to be stronger that effectiveness due to non-adherence. However, our augmented estimates using inverse probability weights give us values of -.832 and .011 suggesting that having Medicaid coverage significantly reduces physical health scores while weakening the effect of coverage on mental health. These findings do not seem to make sense. One potential reason could be that though augmented estimates using IPW accounts for non-compliance, it only considers observed covariates to do so. The estimator will be biased if there are variables affecting both treatment and outcome but are unobserved in the model.

-Using CACE, our efficacy estimates are indeed larger than our ITT effectiveness estimates ie 1.31 and 2.23. Here, our instrumental variable analysis removes the effect of non-compliance by

controlling for both observed and unobserved confounders, giving us an approximately unbiased estimate.

References

Baicker K, Taubman SL, Allen HL, Bernstein M, Gruber JH, Newhouse JP, Schneider EC, Wright BJ, Zaslavsky AM, Finkelstein AN and the Oregon Health Study Group (2013) The Oregon Experiment - Effects of Medicaid on Clinical Outcomes, *New England Journal of Medicine* **368**:1713-1722, DOI: 10.1056/NEJMsa1212321

Public dataset citation: Finkelstein A, Baicker K, Taubman S, Wright B, Bernstein M, Gruber J, Allen H, Newhouse JP, Schneider E, Zaslavsky A (2018), Replication Data for: Oregon Health Insurance Experiment, https://doi.org/10.7910/DVN/SJG1ED, Harvard Dataverse, V1