Early Mental Health Benefits of Medicaid: Evidence from the First Six Months of the Oregon Health Insurance Experiment

A Policy and Program Evaluation Report

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ECO726: Policy and Program Evaluation
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December 2024

ABSTRACT

While the Oregon Health Insurance Experiment (OHIE) demonstrated significant mental health benefits of Medicaid after two years, less is known about potential early impacts of coverage. This project examines whether mental health improvements emerge within the first six months by analyzing OHIE's baseline and six-month survey data. Using causal forest methodology and a constructed mental health proxy measure, the findings reveal modest average treatment effects (-0.008 ± 0.025) but detectable benefits among the lowest-income recipients, with positive effects in households below $2,500 annual income $CATE = (0.00642), SD = (0.0389)$. These results suggest that Medicaid's mental health benefits may begin accruing earlier than previously documented, particularly among the most economically vulnerable recipients.

1 INTRODUCTION

The Oregon Health Insurance Experiment (OHIE) demonstrated through its randomized design that Medicaid coverage significantly reduces depression rates among low-income adults after two years (Baicker et al., 2013). However, less attention has been paid to potential mental health improvements during the initial months of coverage. Understanding whether benefits begin to emerge earlier could inform expectations about Medicaid's short-term impact on mental health outcomes.

This project analyzes data from the baseline and six-month OHIE surveys to investigate early mental health effects. The analysis employs a proxy measure constructed from three standardized components: *mental health bad days*, *depression diagnosis*, and *general health status*. This approach enables examination of changes in mental wellbeing during the first six months of coverage.

The methodology employs causal forest techniques (Athey and Wager, 2018) to estimate both average and heterogeneous treatment effects. While overall effects at six months are negligible, the results reveal early benefits among the very lowest-income recipients. Specifically, households with annual incomes below $2,500 show small but positive effects, while higher-income groups experience negligible or slightly negative effects. These findings suggest that Medicaid's impact on mental health varies by economic vulnerability and may begin earlier than previously documented.

1.1 Research Question

Does Medicaid coverage causally reduce depression rates among low-income adults within the first six months of coverage?

2 METHODS

2.1 Data

The analysis draws on publicly available datasets from the Oregon Health Insurance Experiment (OHIE), which used a randomized lottery in 2008 to allocate Medicaid coverage among low-income adults in Oregon. While the OHIE included PHQ-2 scores in its two-year in-person survey, this study utilizes the baseline and six-month survey datasets to examine earlier effects. The analysis sample includes 5,635 observations (2,818 unique individuals, with 1,011 treated and 1,741 control at baseline) with complete data at both timepoints.

Mental health outcomes were measured using a standardized proxy combining three indicators: mental health bad days, depression diagnosis, and general health status. Each component was standardized to z-scores and weighted equally in the final measure. While this proxy has not been validated against clinical measures like PHQ-2, it incorporates multiple dimensions of mental health status that likely reflect underlying depression severity. The standardization process ensures each component contributes equally to the final score, with higher values indicating worse mental health outcomes.

Key covariates include demographic variables (age, gender, race), socioeconomic indicators (employment, education, household income), and health measures (general health status, physical and total bad health days). The sample was predominantly white (86.8%), female (58.3%), with an average age of 59 years. These variables were employed in both propensity score matching and causal forest models to account for confounding and explore effect heterogeneity.

2.2 Analysis

2.2.1 Covariate Adjustment

The analysis employed a random forest model to estimate propensity scores for Medicaid assignment, accounting for potential confounding and ensuring comparability between treatment and control groups. The model included key demographic variables (age, gender, race), socioeconomic indicators (education, income), and health-related factors. Variable importance scores confirmed the relevance of these covariates, with age and income categories emerging as the strongest predictors. Initial balance checks revealed no statistically significant differences in baseline characteristics between groups.

2.2.2 Outcome Model

To examine how Medicaid's mental health benefits varied among different income levels within the low-income population, I employed causal forest methodology following Athey and Wager (2018). While traditional approaches might only reveal average effects across all recipients, causal forest allow us to detect variations in treatment effects across subgroups—of paticular interest given that even within a low-income population, the impact of Medicaid might differ substantially between those at different economic levels.

The method addresses Holland's (1986) fundamental problem of causal inference—that individuals cannot be observed both with and without Medicaid simultaneously—by constructing credible counterfactuals based on observed characteristics. The causal forest was trained using the same covariates as the propensity score model, with the primary outcome defined as the change in *phq_proxy* scores from baseline to 6 months.

The propensity score matching and causal forest analyses complement each other in this project. While matching helps establish the validity of group comparisons by balancing observed covariates, the causal forest extends this analysis by revealing how treatment effects vary across these same characteristics. Notably, both methods highlight the importance of income, with matching showing some residual income differences ($p = 0.0473$) and the causal forest identifying income as a key predictor of treatment effect heterogeneity (importance score 0.151). The consistency across methods strengthens our confidence in the role of income in moderating Medicaid's mental health benefits.

2.2.3 Statistical Inference

Statistical inference was conducted by assessing the significance of treatment effects and subgroup differences. The causal forest model produced individual-level treatment effect estimates, which were aggregated to compute the ATE (-0.008 ± 0.025). Income category emerged as the third most important predictor of treatment effect heterogeneity (0.151), as shown in Figure 1.

What does this mean in practical terms? While we found almost no effect of Medicaid on depression when looking at everyone together, the analysis revealed that income level strongly influences who benefits from Medicaid coverage. In fact, when we tested whether these differences across income groups could be due to chance, we found extremely strong evidence that they weren't ($F = 15.53, p < 2e^{-16}$). This tells us something crucial: Medicaid's effectiveness in reducing depression varies significantly depending on a person's income level, even within this low-income population.

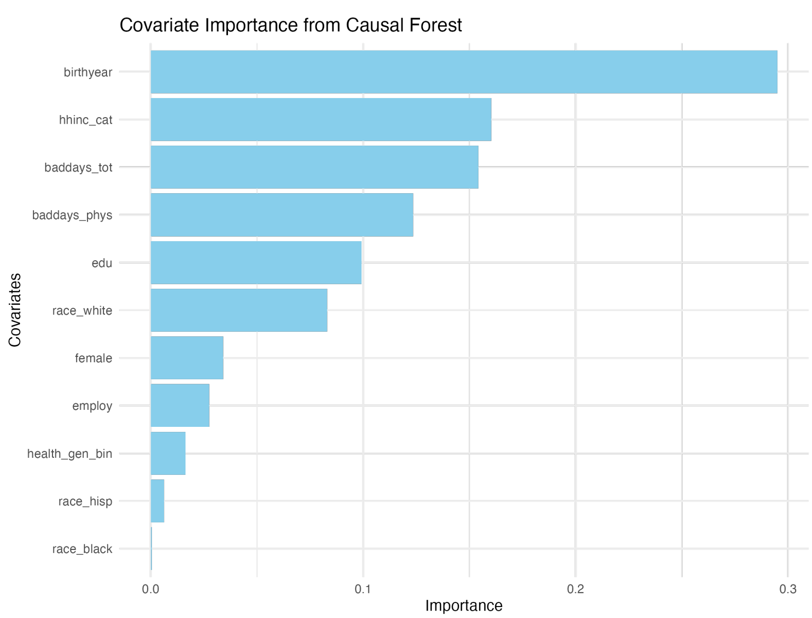

Figure 1. Covariate Importance from Causal Forest

3 RESULTS

3.1 Assessing CIA

To ensure reliable results, we needed to validate that our treatment and control groups were truly comparable. Our statistical matching process successfully aligned most characteristics between people who received Medicaid and those who didn't. The matching particularly improved the balance of key demographic factors, with negligible differences remaining in age (0.0265), gender (0.0005), and education levels ($p = 1.000$).

More technically, this validation of the Conditional Independence Assumption employed optimal propensity score matching between treatment ($n = 2,051$) and control groups ($n = 3,584$), reducing the standardized mean difference in propensity scores from 0.1755 to 0.0202. While some health measures showed persistent imbalance after matching (physical health days: -0.1163), and a marginally significant difference remained in household income ($p = 0.0473$), these differences stayed below conventional thresholds for concerning imbalance. Nevertheless, these small remaining differences warrant careful consideration when interpreting how Medicaid's effects vary across income levels.

Table 1. Baseline Covariate Balance Between Treated and Control Groups Post-Matching

Covariate	Treated (Mean ± SD)	Control (Mean ± SD)	p-value
Age	58.4 ± 12.1	58.4 ± 12.4	0.904
Female	0.57 ± 0.49	0.57 ± 0.49	0.950
Race (White)	0.88 ± 0.33	0.84 ± 0.36	0.00188
Employment	0.51 ± 0.50	0.49 ± 0.50	0.0918
Education	2.37 ± 0.89	2.37 ± 0.89	1.000
Household Income	7.51 ± 4.86	7.21 ± 4.94	0.0473

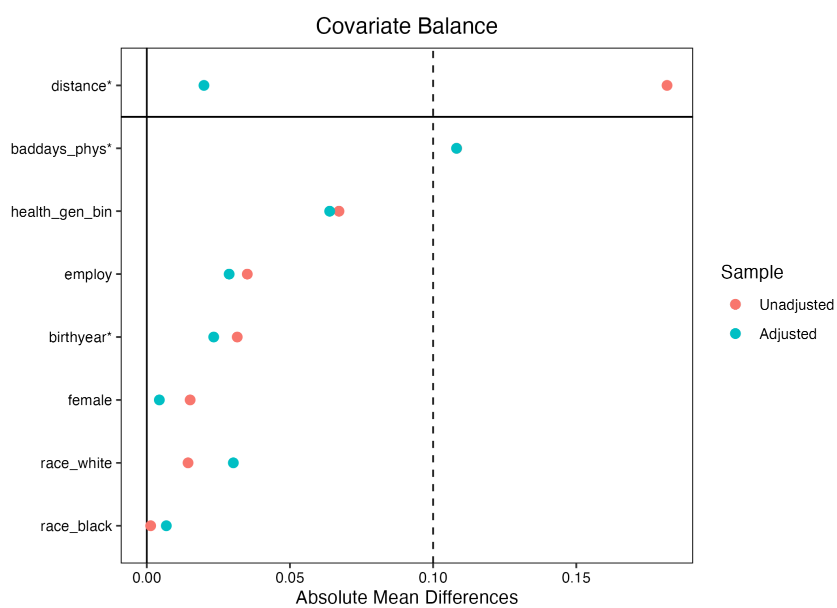

Figure 2. Covariate Balance Before and After Matching

3.2 Policy Impact Estimates

3.2.1 Primary Estimates

The causal forest analysis revealed a minimal overall impact of Medicaid on depression, with an Average Treatment Effect (ATE) of -0.008 ± 0.025 on our standardized mental health measure. Importantly, when examining which factors most strongly predicted variation in Medicaid's effectiveness, *income* emerged as one of the top three predictors (0.151), surpassed only by age (0.297) and total days of poor health (0.164). This finding reinforced our earlier evidence that income plays a crucial role in how Medicaid affects mental health outcomes.

3.2.2 Subgroup Analysis

A deeper examination of income-based differences revealed something of interest in Medicaid's effectiveness ($F = 15.53, p < 2e^{-16}$) within income sub-groups. While the effects were modest in size, they showed a clear trend across income levels. Among the poorest participants - those reporting no income or earnings below $2,500 annually - Medicaid had small but positive effects on mental health (CATEs of 0.00642 and 0.00584 respectively). However, this benefit gradually diminished as income increased, eventually becoming slightly negative for those earning more than $5,000 annually ($-0.00618) and reaching its most negative effect ($-0.0194) among those earning $20,001-$22,500.

Figure 3 illustrates this income gradient through boxplots. While the distributions overlap considerably (visible in the wide ranges, e.g., -0.0970 to 0.131 for the $0 bracket), the trend in mean effects suggests Medicaid's mental health benefits concentrate among lower-income recipients.

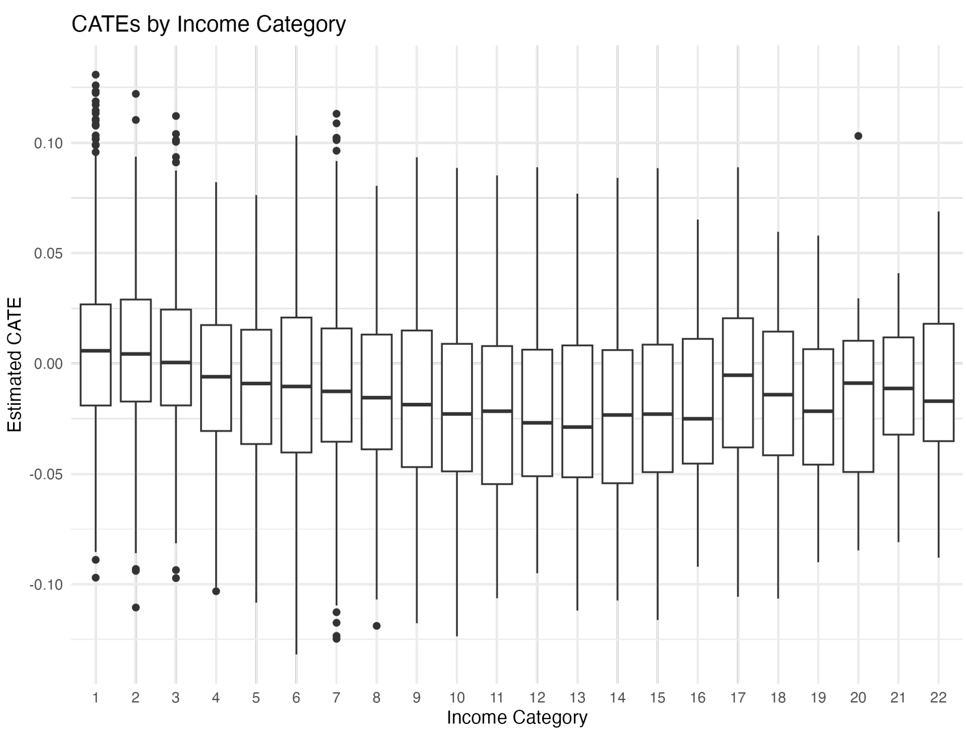

Figure 3. CATEs by Income Category

4 DISCUSSION

4.1 Results Interpretation

While we found little effect when looking at all recipients together (-0.008 ± 0.025), a more detailed examination revealed that Medicaid's effectiveness varies depending on recipients' income levels. The program shows its greatest promise among those most financially vulnerable - people reporting no income saw small but positive improvements in their mental health ((0.00642)). However, these benefits diminish and eventually become slightly negative for those earning more than $5,000 annually. While these effects are modest, they demonstrate an important finding: Medicaid appears to provide targeted mental health support precisely where it's needed most - among those facing the greatest economic hardship.

The robustness of these findings is supported by strong covariate balance achieved through optimal matching, though some caution is warranted due to persistent racial imbalance $(p = 0.00188)$ and marginal income differences $(p = 0.0473)$. The substantial overlap in CATE distributions across income groups suggests considerable individual-level variation in treatment response.

4.2 Policy Implications

These results suggest that policymakers might achieve the greatest mental health benefits by focusing Medicaid expansions on the most economically vulnerable populations. While the modest size of these effects might not justify expanding Medicaid to all income levels based on mental health benefits alone, there's clear evidence that targeting expansions to households earning less than $5,000 annually could yield meaningful improvements in mental health outcomes.

4.3 Limitations

Our study faced several important challenges. First, because we had to construct our own measure of depression from available data, we might be underestimating Medicaid's true impact. Second, the small remaining differences between our treatment and control groups in terms of race and income, while not large enough to invalidate our findings, suggest the need for careful interpretation. Finally, while we found clear patterns across income groups, the wide range of individual responses (from (-0.0970) to (0.131)) reminds us that Medicaid's mental health benefits can vary substantially from person to person.

4.4 Future Steps

Moving forward, researchers should explore how Medicaid's mental health benefits might vary across other important dimensions, particularly race and gender, given their crucial role in mental health outcomes. Future studies would benefit from using direct clinical measures of depression and tracking outcomes over longer periods. Additionally, analyzing the cost-effectiveness of different targeting strategies could help policymakers determine the most efficient income thresholds for Medicaid expansion.