Weight of Health Coverage: Exploring the Effects of Health Insurance on Obesity Rates

Ilkin Umut Melanlıoğlu, Ebubekir Karamustafa
imelanlioglu21@ku.edu.tr, ekaramustafa20@ku.edu.tr

Abstract— **Although the catalysts behind the increasing global obesity rates have long been the subject of various academic debates, a large portion of those discussions aim to explain the phenomenon from a societal or consumeristic perspective. While most of those studies typically acknowledge the availability of medication and medical services as a confounding factor, the subject populations are often assumed or set to have an even distribution of healthcare coverage.**

This report examines the impact of having public health insurance on obesity and outlines possible confounding variables. Using data from a Randomized Control Trial experiment, we calculate the Average Treatment Effect of having health insurance on being obese. To assess whether this relationship is specific to obesity, we perform the previous calculations for several related medical conditions, i.e. diabetes, high cholesterol, and hypertension.

I. Introduction

This project aims to investigate the causality of the complex relationship between having health insurance and obesity. By employing several unsophisticated data analysis tools over a pre-existing dataset, we try to convey an intuitive understanding of the causal connection between health insurance and obesity rates.

A. Background

Starting from the 1970s, scientific studies have uncovered the unprecedented increase in global obesity rates over the past decades. While this sudden rise in obesity paved the way for fruitful discussions about various eating habits and the importance of having a balanced diet, it also led to a troublesome demographic shift – a 2012 empirical study conducted in the US predicted an astounding increase of 33% in local obesity rates by 2030 [1]. Apart from a spike in individuals' medical concerns, the uneven shift within the weight categories could seriously damage the social and economic fabric of the populations.

To better understand the root cause of increased obesity rates and to counteract the troubling trend, countless academic and medical institutions have initiated extensive research. In particular, two of the most prominent scientific branches within this research focus have been medicine and economics. Although there is no uniform consensus regarding the cause of obesity within both of the scientific communities, a wide range of obesity factors have been put forward, for example [2],[3].

In fact, the particular viewpoint that has motivated us to undertake this project suggested that having health insurance would give a person an economic incentive to become obese [4]. The argument revolved around the notion that, in a sense, people who are isolated from the medical costs of obesity by having an insurance plan are more likely to develop unhealthy eating habits.

This unorthodox perspective was particularly intriguing because it went directly against our preconceived beliefs regarding the relationship between obesity and health insurance. We believed that the increased availability of medications, medical services, and preventative care through health coverage would gradually decrease a person's probability of being obese.

B. Project Question

Upon further exploring the existing literature on the subject, we were not able to establish a consensus that explained the specific duality of having health insurance. Hence, the logical continuation for us was to put both arguments to the test. The primary question that guides this investigation is whether there is a causal relationship between having health insurance and obesity. To that end, we also analyze the effect of health insurance on similar medical conditions and outline insurance-related confounding variables that play a role in this, possibly complex, relationship.

II. Dataset

To find an answer to our question, we turned our attention to the dataset from the Oregon Health

Insurance Experiment (OHIE). Conducted in 2008, OHIE is a comprehensive study in the field of health economics and policy, designed to evaluate the impacts of public health insurance on health care use and health outcomes among low-income individuals. This study was particularly significant for its findings about the role of health insurance in public health. The findings of the experiment have been used to argue both for and against Medicaid expansion. On the one hand, proponents of the expansion have used the results of the experiment to underscore the benefits of increased healthcare access for low-income individuals. On the other hand, critics have pointed out the study's findings on the limited effectiveness of such programs and disagree with the opinion that the impact was significant enough. Overall, OHIE has significantly enriched our understanding of Medicaid's social, economic, and political impacts, providing new perspectives on the broader implications of health insurance.

Using the OHIE dataset, several studies have also explored the relationship between health insurance and medical conditions such as obesity, diabetes, and cholesterol. These studies focus on how access to health insurance, particularly through the Medicaid Program, influences these medical conditions. For instance, a seminal study [5] investigates whether increased healthcare access leads to any improvement in the treatment of chronic medical conditions. Another paper [6] evaluates the effectiveness of Medicaid coverage by analyzing the various health metrics. These sources often argue that the Medicaid program does not have a significant effect on the treatment of obesity, diabetes, and cholesterol although the diagnosis rates increased with the increased use of health care. We are still willing to seek any causal relationship between obesity and health insurance to test previous findings of the literature and further investigate the reasons behind our findings.

A. Experiment Design

The experiment has been notable among other social policy experiments for its design. Oregon implemented an expansion of its Medicaid program through a lottery system. This approach randomly selected individuals from a waiting list, creating a natural experiment that effectively controls for potential confounding variables, which is rarely achievable in Medicaid studies due to ethical constraints. Participants chosen in the lottery were then offered the chance to apply for Medicaid and if they were accepted, they were enrolled in the program, thus receiving health insurance [7].

B. Technical Details

Complementing the experiment design, Oregon opened a waiting list for its Medicaid program in 2008. 30,000 individuals, out of 74,600 low-income participants, were selected through the lottery system to fill the 10,000 available spots in the Medicaid Program. This study, lasting between 14 and 16 months, used two primary categories of data: administrative and survey data.

The administrative data provided a broad and unbiased overview of Medicaid enrollment, hospital data, and health expenses. A notable advantage of administrative data is its comprehensiveness and minimization of non-response biases, as the data is collected from health institutions. Coupled with the blood, weight, and other medical measurements taken at the final in-person survey, the administrative data provided objective and quantifiable health indicators for the experiment.

In contrast, survey data gathered from ~20,000 individuals from both control and treatment groups, through three follow-up surveys over a year, provided deeper insights into individual health statuses and healthcare utilization. The three mailed surveys, each sent once in 6 months, consisted of randomized recipients and, hence, different respondents. However, despite potential biases due to non-respondents, survey data allowed them to capture more subjective and nuanced health outcomes. Combining these two data types, the administrative and survey data together mitigated their technical limitations. This approach enhanced the study's ability to assess a wide range of outcomes [8],[9].

The final in-person survey, conducted at the end of the 1.5-year-long OHIE, collected the main portion of the survey data used in our investigation through a series of medical measurements and computer-assisted interview questions. Out of the more than 74,599 experiment participants, 20,000 were randomly selected and invited to the in-person survey. For simplicity, approximately half of the invitees were lottery winners and the other half were participants who did not win the lottery. Approximately 8,000 of the invitees missed the interview and 12,000 completed the interview. While the study report considers the effective (weighted) response weight for the control population to be 73.0%, a significant portion (88.6%) of the participants who did not attend the interview were comprised of people who were not enrolled in Medicaid. While the imbalanced distribution of in-person survey participants decreases the effectiveness and reliability of the study's findings, we assume that there was no particular motivation for the two experimental populations to either miss or attend the in-person interview. Moreover, considering that the survey questions were fully answered by more than 10,000 participants, the effects of non-ideal response rates are negligible.

Our analysis mainly focuses on the causal relationship between obesity and health insurance, and how health insurance impacts other medical conditions such as diabetes, high cholesterol, and hypertension. Moreover, integrating administrative and survey data allows us to assess the effectiveness of the Medicaid Program on healthcare utilization, quality of care, and treatment of various medical conditions. This comprehensive approach is crucial for understanding the program's broader implications and causal relationships.

C. Pre-Processing the Data

In order to reduce the workload during the computational stage of the project, we decided to narrow down our focus on a selected subset of the dataset that offered an adequate amount of administrative and survey data for us to derive meaningful insights. However, it was also important to disregard the data that would not either logically or chronologically fit our analysis methods. For instance, given that no weight or BMI-related information was shared within the 3 mailed surveys, our analysis heavily relied on the readings obtained in the final in-person survey; to that end, although there was data collected within 6-month intervals prior to the in-person survey that could suggest a gradual evolution of some confounding variables – such as smoking or diabetes detection – we decided to disregard it due to the chronological misalignment with the rest of the BMI data.

The pre-processing and cleaning of the Oregon Health Insurance Experiment (OHIE) dataset was conducted in Julia, a relatively modern and user-friendly programming language. While the original dataset is publicly available as a collection of DTA files, those were initially converted to CSV files for further compatibility with Julia's data analytics tools. Given that the OHIE dataset consisted of hundreds of variables across 7 different CSV files, the primary pre-processing step was determining the ones that contained information relevant to our project question. To that end, the ones including the mailed survey data and experimental patterns were not selected. The following three sub-datasets were used in the subsequent stage of the project:

- Descriptive variables (age, gender, etc.)
- Emergency Department (ED) variables
- In-Person Survey Readings

These 3 datasets were combined through a common identifying variable, i.e. person_id. The following step was to eliminate the variables that had a poor logical connection to our proposed question; these variables included ones such as the interviewer number and language of the survey.

Then, in order to be able to use the necessary statistical operations, we identified the variables with non-numeric entries and cast them into floating-point numbers. For example, the entries of a column that included "Yes" and "No" were cast into 1.0 and 0.0, respectively. The last step was to identify and filter out the individuals whose information was NaN or missing under one or more key columns, such as BMI or Hemoglobin A1C.

III. Methodology

To obtain meaningful and generalizable insights into the relationship between having health insurance or, in this case, being enrolled in Medicaid and the obesity rates, we use a simple Average Treatment Effect (ATE)-based approach. We believe that such an approach is particularly efficient since the OHIE is an RCT-based experiment, enabling us to disregard the effects of selection bias, i.e. selections on treatment and levels. In other words,

$$ATE = Observational\,Effect \qquad (1)$$

Moreover, working with an RCT experiment enables us to assume that the effects of confounding variables are distributed evenly among control and treatment groups. Hence, although numerous variable measurements were not collected at the start of the experiment, we were able to neglect the absence of prior information regarding those variables by assuming that the measurements given by the control group at the final in-person survey could serve as a baseline from the start of the experiment. For instance, despite not having any prior information regarding the BMIs of the participants, we calculated the average treatment effect by subtracting the average in-person measured BMIs of the control group from the treatment group.

However, it is important to mention that we performed a significant modification to the original experimental design when forming our investigation. Unlike the OHIE, which considers people selected in the lottery to form the treatment population, we formed our treatment group out of individuals who were selected through the lottery and also approved by the experimenters to receive Medicaid. While proceeding with the original experiment design and estimating the Local Average Treatment Effects (LATEs) of being enrolled in Medicaid was certainly a viable option, we decided to proceed with a simpler design, where we included only the beneficiaries of Medicaid in the treatment group. Hence, we ignore the selection effects during the post-lottery application review procedure for increased simplicity and interpretability. Nevertheless, we understand that our design creates a significant imbalance between the population sizes of the two groups and hinders the reliability of our findings.

A. Project Hypotheses

We began our study by contrasting the two aforementioned hypotheses regarding the impact of health insurance on obesity. The first hypothesis suggests that by having health insurance that significantly reduces, or nullifies, the medical costs of being obese one with health insurance can be more susceptible to developing obesity. The unhealthy eating habits associated with this insurance-related economic incentive could contribute to higher obesity rates among those with health insurance.

Conversely, our second hypothesis suggests the opposite – health insurance could lead to a decrease in obesity rates. This idea is built upon the assumption that health insurance provides significantly greater access to medical resources and essential care. With this access, individuals are more likely to seek medical care and guidance regarding their weight and diet, improving their health and potentially leading to weight loss. This could lead to improved overall health outcomes and a noticeable decrease in obesity rates among people with health insurance.

TABLE I

The Sample Means, Standard Deviations, and Average Treatment Effect of BMI and Related Medical Conditions. The Numbers Shown in the Parentheses Are the Variances.

Variable	In-Person Survey Participants			
	Treatments	Controls	ATE	% ATE
BMI	29.72 (60.43)	29.80 (56.70)	-0.08	-0.27%
Obesity Rate (%)	40.09	41.19	-1.10	-2.67%
BMI (Male Population)	28.83 (43.92)	29.02 (43.68)	-0.19	-0.68%
BMI (Female Population)	30.41 (72.57)	30.42 (66.21)	-0.01	-0.29%
Hemoglobin A1C	6.65 (0.33)	6.71 (0.40)	-0.06	-0.87%
Total Cholesterol	211.02 (1158.97)	213.91 (1121.44)	-2.89	-1.37%
Systolic Blood Pressure	129.88 (275.97)	130.35 (278.60)	-0.47	-0.36%
Diastolic Blood Pressure	82.32 (144.34)	83.15 (144.94)	-0.82	-0.99%
Number of Participants	1892	9677	-	-

B. Findings

Our analysis began with a comparative assessment of the mean BMI for both groups. We examined the obesity rates in each group, as outlined in Table 1. Interestingly, the ATE value for the BMI remained relatively minimal (-0.08), which comprised a -0.27% difference compared to the average control group BMI, suggesting a negligible difference in BMI due to health insurance coverage. Similarly, the obesity rates, obtained by calculating the percentages of individuals whose BMI is or exceeds 30.0, showed no significant difference between the treatment and control groups (Table 1). Note that the body mass index of 30.0 was not selected arbitrarily and is a universally used threshold for obesity, set by the Centers for Disease Control and Prevention, or CDC [10].

To further investigate the treatment effect, we partitioned the dataset into male and female participants and analyzed the ATE for BMI for those subgroups. This approach aims to seek any potential gender-specific impacts of having health insurance on obesity. However, the differences between control and treatment populations are similar for both of the gender groups – yielding ATE values of -0.19 for males and -0.01 for females. Although the average BMI levels of males being more affected by health insurance and their having a much lower variance compared to that of women is certainly interesting, we were not able to establish a strong causal connection between gender and the effect of health insurance on obesity.

Then, in order to see whether the BMI levels of different age groups were affected differently from having health insurance, we decided to check the age vs BMI distribution among the two experiments

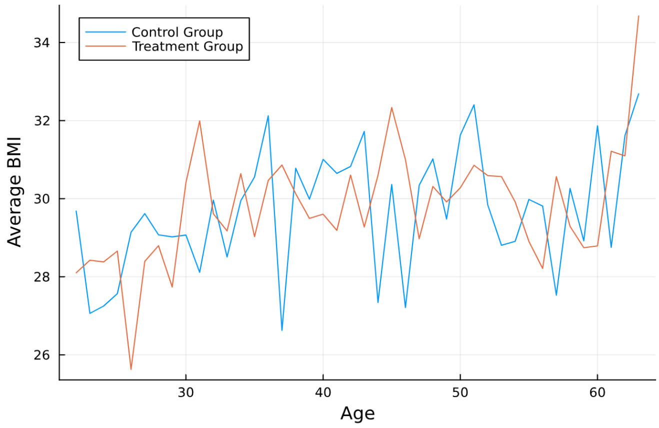

Fig. 2 A simple line graph showing the average Body Mass Index of Control and Treatment groups at each age.

groups. To that end, knowing that the amount of people in the control group was almost 5 times that of the treatment group, we selected a random subset of the control group that matched the size of the treatment one and created the scatter plots for both of the populations (Fig 1, Fig3).

Although one can observe that there are not many noteworthy visual differences in the age vs BMI distributions among the two populations that could suggest a causal treatment effect, reading the scatter plots is somewhat challenging due to the sheer amount of data points. To increase the interpretability of the data, we look at the mean BMIs at each age within the two groups (Fig 2).

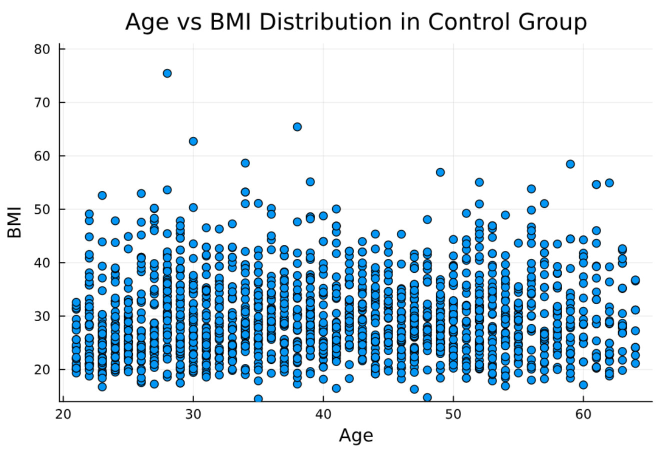

Fig. 1 A scatter plot based on the ages and BMIs within a random subset of the control group

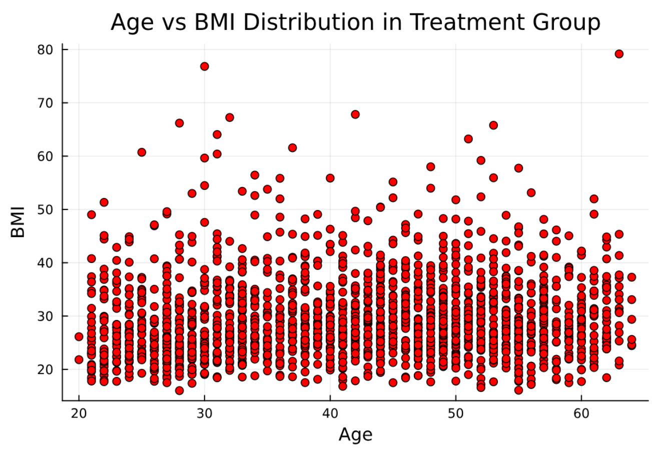

Fig. 3 A scatter plot based on the ages and BMIs within the treatment group.

Observe how although the difference in average BMI shows strong variation across different ages, both of the mean BMI graphs do not follow a general trend; in fact, even though there are some noteworthy average BMI differences within an age interval, such as between ages 30 and 32, such intervals are often very short and the difference often disappears within the next 2-3 years. This suggests that even the greatest differences in average BMI are most likely caused by the randomized nature of the control group's scatter plot.

Therefore, it becomes evident that a statistically strong connection between having health insurance and BMI cannot be established. Although the treatment group is observed to have consistently but marginally lower BMIs, such differences in BMI and obesity rates were not great in magnitude. Considering that the Average Treatment Effect is negligibly low, one can infer that there is not a strong causal relationship between obesity and being enrolled in Medicaid, or having health insurance.

Clearly, both of our initial hypotheses are not supported by the findings. Since the lack of a trend or strong treatment effect is certainly unexpected, we decided to perform similar computations for several obesity-related medical conditions: diabetes, high cholesterol, and hypertension. Considering that final in-person measurements have been taken for those medical conditions, a lack of trend or treatment effect could support the absence of empirical evidence suggesting a causal relationship between health insurance and obesity. In fact, the measurements and the estimated ATEs for those three medical conditions indicate a similar story to that of BMI and obesity (Table 1). Looking at Table 1, we can see that there was minimal difference in Systolic and Diastolic Blood Pressures, Total Cholesterol, and Hemoglobin A1C levels between the two experiment groups. However, it is important to note that, unlike obesity which can be technically cured by losing weight, these three medical conditions are often chronic and do not have a definitive 'cure'. Despite the different treatment perceptions that can be associated with those three illnesses, an average treatment group participant benefited by approximately 1.00% within those three medical conditions by being enrolled in Medicaid, which is substantially lower than what we were expecting. This lack of change within the treatment group parallels the ATE-based conclusion for obesity and further undermines the effectiveness of Medicaid.

Although one could argue that such results obtained from the OHIE cannot be generalized to health insurances other than Medicaid, we believe that, due to the well-renowned randomized control design and meticulous methodological approach throughout the experiment, the findings hold somewhat significant merit and can be used outside of the context of Medicaid. Thus, notwithstanding the unexpected results, we shift our focus to a new question: what could be the possible explanation for this lack of treatment effect? To explore this, we proposed two additional hypotheses.

The first new hypothesis emerges from a consideration of health insurance utilization. It is possible that some individuals do not adequately utilize their health insurance despite having access to medical care. This idea suggests that despite being insured through their enrollment in Medicaid, the participants in the treatment group did not actively seek medical care or take recommended prescription medications. Such a scenario could explain why considerable health improvements for people in the treatment group were not observed during final in-person measurements despite them having health coverage for more than 12 months leading up to the in-person survey.

Our second hypothesis considers the effectiveness of the Medicaid program itself. It proposes that perhaps the program is not sufficiently effective in improving the health status of individuals diagnosed with relevant medical conditions. This idea paves the way for a critical examination of the Medicaid program's structure and implementation, questioning whether it addresses the complex medical needs of its participants. One potential problem could be inadequate coverage for various medications under Medicaid's public health insurance. Alternatively, it might be due to regional issues, such as a lack of quality care in Oregon.

TABLE 2
THE SAMPLE MEANS, AND AVERAGE TREATMENT EFFECT OF UTILIZATION AND QUALITY METRICS.

Variable	In-Person Survey Participants			
	Treatments	Controls	ATE	% ATE
Got All Needed Medical Care (0-1)	0.66	0.60	0.06	10.34%
Got All Needed Medication (0-1)	0.77	0.73	0.04	6.31%
Quality of Medical Care (1-5)	3.08	2.62	0.46	17.26%
Number of Doctor Visits	8.04	6.34	1.70	26.75%
Number of Hospitalizations	0.35	0.24	0.11	43.50%
Number of Emergency Department Visits	0.58	0.42	0.16	38.46%
Number of Participants	1892	9677	-	-

To evaluate the first new hypothesis, we shifted our analysis to a set of variables that might uncover some useful health insurance utilization patterns. These variables can be classified into two groups: 'utilization' and 'quality' metrics. For the utilization metrics, we have incorporated three key variables from the administrative data: the number of doctor visits, overnight hospitalizations, and emergency department visits over the past 12 months. On the other hand, quality metrics are composed of three variables extracted from the in-person survey data. These variables capture subjective assessments of individuals such as the perceived quality of medical care and whether individuals report having received all necessary medical care and medications.

Despite their subjective nature, the quality metrics offer valuable insights into understanding the perceived effectiveness, satisfaction, and general accessibility of health insurance provided by Medicaid. According to the data in Table 2, insured individuals report higher satisfaction with their health care – the average value for the Quality of Medical Care within the treatment group was 17.26% greater than that of the control group. Moreover, the treatment group has notably greater percentages of individuals who report having received all necessary medical care and medications – 10.34% and 6.31%, respectively.

However one can argue that statistical improvements in quality metrics cannot alone claim that Medicaid provides sufficient coverage and health services. In a sense, that is true – individual satisfaction regarding the benefits of health coverage can often be highly misleading due to the subjective nature of their personal needs and experiences. Nonetheless, the limitation regarding the interpretation of the subjective variables does not change the observable fact that the treatment group demonstrates a higher degree of satisfaction compared to the control group.

Moreover, the utilization metrics emphasize another important trend: individuals with health insurance exhibit a statistically significant increase in medical care utilization. Notably, the treatment group reported a 26.75% rise in doctor visits and a 43.50% rise in hospitalizations, indicating that health insurance incentivizes individuals to seek medical care more actively. The significant increase in hospitalizations, which is indicative of treatments for serious conditions that require overnight care, highlights the critical role of accessible care for those with severe medical conditions. This, coupled with a 38.46% increase in emergency department visits as shown in Table 2, suggests that although insured individuals visited the doctors more frequently (26,75%), a greater difference between the treatment and control group occurred during the overnight hospitalizations and ED visits. This indicates that people with severe medical conditions benefited more from being ensured. Compared to ED visits or overnight stays in the hospital, general doctor visits are much more common for people suffering from obesity-related diseases; therefore, a lower difference in the number of doctor visits could serve as a possible explanation for the relatively weak treatment effect of being enrolled in Medicaid on obesity.

Overall, the combination of utilization and quality metrics portrays a comprehensive picture of how the treatment group engages with the healthcare system under Medicaid and helps us relate these patterns to the previous results for obesity. Importantly, the increased satisfaction and active engagement with medical services observed in the treatment group contradicts our hypothesis suggesting a lack of healthcare utilization.

However, another approach for evaluating the effect of having health insurance on obesity and related medical conditions would be to check the differences in diagnosis rates. Unfortunately, since the study dataset does not provide prior information

TABLE 3
THE SAMPLE MEANS AND AVERAGE TREATMENT EFFECT OF DIAGNOSIS RATES OF RELATED MEDICAL CONDITIONS.

Variable	In-Person Survey Participants			
	Treatments	Controls	ATE	% ATE
Diabetes Diagnosis Rate (%)	2.64	1.56	1.08	68.65%
High Cholesterol Diagnosis Rate (%)	9.79	6.42	3.37	52.82%
Hypertension Diagnosis Rate (%)	9.54	6.91	2.63	38.39%

about the individuals' weights and BMIs from the start of the experiment, we are not able to construct a diagnosis metric for obesity. Hence, we check the differences in the diagnosis rates for diabetes, high cholesterol, and hypertension. While calculating the ATE on in-person medical measurements for the individuals who have been diagnosed with these three medical conditions was the metric that we initially considered, the number of diagnosed individuals in both of the subgroups turned out to be unexpectedly low, leading us to focus on the diagnosis rates instead. The diagnosis rates were obtained by calculating the percentage of people in the control and treatment groups who had been diagnosed with their respective medical conditions within the duration of the experiment and not prior to the experiment. For instance, the Diabetes Diagnosis Rate (Table 3) relates to the percentage of previously undiagnosed individuals who have been diagnosed with diabetes during the OHIE.

In fact, Table 3 reveals that, across those three medical conditions, undiagnosed individuals are much more likely to be diagnosed with the respective medical condition after obtaining health insurance. For instance, the differences in diagnosis rates for high cholesterol and diabetes were 52,82% and 68.89%, respectively. Such differences in diagnosis rates align with our previous observations that suggested a 26.75% increase in the number of hospital visits for insured individuals. This correlation implies that the increased access to healthcare services was highly beneficial to insured individuals in terms of understanding their health statuses.

IV. CONCLUSION

Conclusively, our investigation did not reveal a statistically significant causal relationship between health insurance and obesity. Upon analyzing the underlying reasons for the lack of causality, we discovered that individuals with health insurance actually showed higher levels of healthcare utilization and that the insured individuals showed notable awareness and greater satisfaction regarding the increased availability of health services (Table 2). The increased level of healthcare utilization was also reflected in Table 3, where we saw that, most likely due to the increased number of doctor visits, a previously undiagnosed individual is, at times, 68% more likely to be diagnosed after obtaining medical insurance.

Although there were no significant improvements over in-person measurements for related medical conditions such as diabetes, high cholesterol, and hypertension, we believe that it would be misleading to claim Medicaid or health insurance is ineffective based solely on these findings. Considering that our follow-up computations revealed improved diagnosis rates, more prevalent medication intake, greater number of doctor visits, ED visits, and hospitalizations for the insured participants, numerous other potential factors should be factored in for us to properly evaluate the efficacy of the program and understand the underlying reasons behind the lack of in-person medical measurement differences.

The complex nature of medical treatment outcomes – often requiring extended periods and a comprehensive approach, including lifestyle changes – was not fully explored in our analysis. We focused on evident patterns within the dataset rather than extensive and detailed interpretation of the evaluation of variables. It is important to note that each variable might require distinct approaches in analyzing their outcomes. Moreover, our analysis was based on a limited sample size from the larger population, with only ~10,000 participants. This restricts the logical extent to which we can extrapolate our findings on all Medicaid recipients in Oregon or across the United States. Additionally, as mentioned previously, while the lottery selection for Medicaid was random, potential biases in the Medicaid application assessments could suggest a necessity for constructing a Wald estimator for calculating the Local Average Treatment Effect (LATE) to consider selection bias. In this study, we assumed no such bias, thus calculating the Average

Treatment Effect without considering selection effects in Medicaid application assessments.

Despite these limitations, one finding remains clear: individuals with health insurance reported greater satisfaction with their healthcare experience and increased utilization of healthcare services. However, we found no direct causal relationship – neither positive nor negative – between health insurance and obesity. These insights emphasize the multi-dimensional nature of healthcare impact and the necessity for further studies into the complex dynamics of health insurance and health outcomes.

References

[1] E. A. Finkelstein et al., “Obesity and severe obesity forecasts through 2030,” American Journal of Preventive Medicine, vol. 42, no. 6, pp. 563–570, 2012. doi:10.1016/j.amepre.2011.10.026

[2] J. Cawley, “An economy of scales: A selective review of obesity’s economic causes, consequences, and solutions,” Journal of Health Economics, vol. 43, pp. 244–268, 2015. doi:10.1016/j.jhealeco.2015.03.001

[3] B. Swinburn, G. Sacks, and E. Ravussin, “Increased food energy supply is more than sufficient to explain the US epidemic of obesity,” *The American Journal of Clinical Nutrition*, vol. 90, no. 6, pp. 1453–1456, 2009. doi:10.3945/ajcn.2009.28595

[4] J. Bhattacharya, K. Bundorf, N. Pace, and N. Sood, “Does Health Insurance Make You Fat?,” *NBER Working Paper Series*, Jul. 2009. doi:10.3386/w15163

[5] H. Allen and K. Baicker, “The effect of Medicaid on care and outcomes for chronic conditions: Evidence from the Oregon Health Insurance Experiment,” NBER Working Paper, 2021. doi:10.3386/w29373

[6] K. Baicker *et al.*, “The Oregon Experiment — effects of medicaid on clinical outcomes,” *New England Journal of Medicine*, vol. 368, no. 18, pp. 1713–1722, 2013. doi:10.1056/nejmsa1212321

[7] “Oregon Health Insurance Experiment,” National Bureau of Economic Research, https://www.nber.org/programs-projects/projects-and-centers/oregon-health-insurance-experiment?page=1&perPage=50 (accessed Dec. 20, 2023).

[8] A. Finkelstein et al., “The Oregon Health Insurance Experiment: Evidence from the first year”, 2011. doi:10.3386/w17190

[9] A. Finkelstein et al., “The Oregon Health Insurance Experiment: Evidence from the In-Person Interviews”, 2012.

[10] “Defining Adult Overweight & Obesity,” Centers for Disease Control and Prevention, https://www.cdc.gov/obesity/basics/adult-defining.html#:~:text=If%20your%20BMI%20is%2018.5,falls%20within%20the%20obesity%20range (accessed Dec. 22, 2023).