THE OREGON HEALTH INSURANCE EXPERIMENT: ANALYZING GOVERNMENT-PROVIDED HEALTH INSURANCE TAKE-UP ACROSS DEMOGRAPHIC VARIABLES

by

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In 2008, Oregon policymakers offered low-income and uninsured residents access to health insurance called the Oregon Health Plan Standard through a lottery rationing device. Studies done in conjunction with the Oregon Health Insurance Experiment to examine subsequent outcomes use an instrument variable design where assignment to the treatment group (selection in the lottery) serves as a proxy for actual treatment (enrollment in health insurance). Consequently, previous research assumes that the entire treatment group act as "compliers" and apply for enrollment. This thesis thus examines the likelihood that an individual selected via the lottery system applied to the Oregon Health Plan across demographic variables such as racial and ethnic identification, gender, income strata, educational attainment, employment status, age, household size, and geography. This thesis finds statistically significant evidence to support that take-up of the Oregon Health Plan Standard is non-random across demographic traits.

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Introduction

In 2008, Oregon policymakers offered low-income and uninsured residents the chance to enroll on a subsidized health insurance plan, called the Oregon Health Plan Standard. The catch? Oregon policymakers utilized a lottery system to ration the scarce resource, so only residents who were selected in the lottery were given the chance to apply for state-sponsored Medicaid. Unbeknownst to policymakers, the random assignment of health insurance to previously uninsured individuals allowed economists to meaningfully study the effects of health insurance coverage. The research from this event has since been referred to as the Oregon Health Insurance Experiment. Researchers from the Oregon Health Insurance Experiment used an instrument variable regression design where assignment to the treatment group (selection in the lottery) served as a proxy for actual treatment (enrollment in health insurance). Consequently, their results assume that the entire treatment group act as “compliers” and gain coverage. Yet, only 61% of individuals selected in the lottery applied for enrollment on the Oregon Health Plan.

This thesis examines the “non-compliers” with attention to imperfect and non-random policy take-up. Policy take-up refers to the participation of eligible people in social benefit programs such as the Oregon Health Plan. Globally, social benefit programs suffer from low policy take-up, and it is estimated that only 50% of eligible and uninsured adults are enrolled on Medicaid (Allen et al. 2010). High administrative barriers to applying, lack of information about the program and eligibility requirements, and stigma associated with participation are thought to contribute to low policy take-up (Currie 2006; Remler and Glied 2003; Stuber et al. 2000). Furthermore, research suggests that policy take-up is non-random across categories such as minority racial and ethnic identification and non-native English speakers, with both populations experiencing lower rates of policy take-up (DeVoe et al. 2011; Finkelstein and Notowidigdo 2017; Stuber et al. 2000; Doty et al. 2014).

This thesis thus examines the likelihood that an individual selected via the lottery applied to the Oregon Health Plan across demographic variables such as racial and ethnic identification, gender, income strata, educational attainment, employment status, age, household size, and geography. The thesis aims to identify characteristics and demographic traits that significantly affected a person's propensity to apply to the health insurance program. Utilizing a Linear Probability Model and a Logistic Regression Model, this thesis finds statistically significant evidence to support the claim that take-up of the Oregon Health Plan Standard was non-random across the variables measured. Individuals who applied to the Oregon Health Plan at higher rates were older, identified as Asian, had a phone, listed a P.O. Box as their address, were self-employed, signed up other people for the lottery, and signed themselves up for the lottery. On the other hand, the groups experiencing lower levels of policy take-up were female, identified as Black or Native Hawaiian/Pacific Islander, were retirees, were full-time workers, were high school graduates, had larger household sizes, and had higher household incomes. Overall, this thesis considers how policymakers can design policies with the understanding of which groups of people are left out of the enrollment process for social benefit programs, while leading policymakers to consider designing policies that will remove barriers for any disadvantaged groups.

Background

The Oregon Health Plan

In 1990, 18% of Oregonians did not have health insurance, so the state devised a program to aid their uninsured and low-income residents (Leichter 1999). The need for insurance exceeded Oregon's available resources, so it was imperative that the state create an efficient system to maximize the capacity of the program and minimize costs. Oregon pioneered a solution–the Oregon Health Plan–at the same time many states were scaling back Medicaid.

The most significant element of the new program included expanding Medicaid eligibility to each Oregonian below the federal poverty line. At the federal level, people qualified for Medicaid if they met both financial and categorical eligibility requirements. During the 1990's, only people who had incomes that were 58% of the federal poverty line financially qualified for Medicaid. In addition, a person had to identify as one of the following to be categorically eligible: a child, a pregnant woman, disabled, a parent of an eligible child, or elderly. The Oregon Health Plan (OHP) expansion removed the categorical eligibility barrier and increased the minimum financial eligibility thereby increasing Medicaid enrollment by an estimated 130,000 people in Oregon (Leichter 1999). President Bill Clinton approved the plan on March 20, 1993, and uninsurance rates fell 7 percentage points to 11% in 1996 because of the program and a robust economy (Allen et al. 2013).

Oregon experienced significant budget deficits in the subsequent years until 2003 which led lawmakers to scale back the program as the enrollment peaked at

110,000 enrollees (Finkelstein et al. 2010). The program was split into the Oregon Health Plan Plus and the Oregon Health Plan Standard, the former being Medicaid for the categorically and financially eligible population according to federal guidelines. The Oregon Health Plan Standard was the program for those who would not normally qualify for Medicaid but had incomes between 58% and 100% of the federal poverty line. Oregon policymakers implemented cost-sharing burdens and reduced benefits for the OHP Standard enrollees to save costs, leading to a 46% reduction in enrollment within a year (Allen et al. 2013). Oregon closed enrollment for the Oregon Health Plan Standard in July of 2004; therefore, the program ceased accepting new enrollees, but continued offering benefits to previously enrolled individuals.

By 2008, only 19,000 enrollees remained on the Oregon Health Plan Standard program despite its capacity for 24,000, which allowed lawmakers to consider opening enrollment. Lawmakers contemplated expanding the program to those with the greatest financial need, although the Centers for Medicare and Medicaid Services denied this option (Allen et al. 2013). Policymakers also decided that a first-come, first-served approach would disadvantage rural Oregonians and the homeless. Instead, Oregon's Medicaid Advisory Committee suggested a lottery system which earned the public and policymakers' vote for the fairest distribution of the resource. Between January and February of 2008, 90,000 people signed up for the chance to be selected for subsidized health insurance through the OHP Standard program (Allen et al. 2013). Public awareness campaigns included mass radio advertisements, press releases, and direct mailers with educational information sent to low-income Oregonians. Individuals could add themselves and/or other eligible individuals in their household to the reservation list by phone, fax, mail, online, or in person.

Oregon policymakers selected 29,834 people in eight random drawings between March and September of 2008. The lottery winners were then eligible to apply for the Oregon Health Plan Standard. Winning the lottery did not grant automatic admission to the program; it only gave selected individuals the opportunity to apply. Lottery winners were sent a two-page application and up to eight supplemental forms and asked to provide the names of all the family members applying for coverage within the household. They were also asked to provide verification of Oregon residence, of U.S. Citizenship, of insurance history for the past six months, of household income, and of their total assets. The form required basic personal information such as name, date of birth, sex, address, phone number, and preferred language of communication. The forms were provided in both English and Spanish. Each lottery winner had 45 days from the time they were selected to submit the application. Of the 29,834 people chosen to submit an application, only 18,123 completed the application process.

Oregon policymakers then verified that the applicants met eligibility requirements. Applicants were required to be between 19 and 64 years old,[1] be residents of Oregon or legal immigrants, be ineligible for Medicaid and/or Medicare, be uninsured for the past six months, have an income below 100% of the federal poverty line, and have total assets below $2,000 (Baicker et al. 2013). Forty-eight percent of those who applied were approved for enrollment.

[1] Children under 19 categorically qualify for Medicaid, so they were eligible for the Oregon Health Plan Plus. Adults over 64 qualify for Medicare.

Oregon policymakers conducted subsequent lottery drawings for selection onto the OHP until 2013 when the Affordable Care Act gave states additional funding for Medicaid programs; therefore, Oregon had enough resources for all eligible people to directly enroll on the program. This thesis will focus on the first year the lottery mechanism was used.

The Oregon Health Insurance Experiment

The Oregon Health Insurance Experiment (OHIE) emerged from the 2008 expansion of enrollment on the Oregon Health Plan Standard through the lottery system. The Principal Investigators who crafted the experiment included Katherine Baicker, Amy Finkelstein, Heidi Allen, Bill Wright, Mira Bernstein, Jonathan Gruber, Joseph Newhouse, Eric Schneider, Sarah Taubman, and Alan Zaslavsky. Together, these researchers completed the most comprehensive study to date on the effects of a change in health insurance status on healthcare utilization, financial hardship, health status, and labor market outcomes.[2] The OHIE Researchers capitalized on the opportunity to study the effects of a random assignment of health insurance, which allowed their studies to benefit from exogeneity.

The researchers found that access to health insurance increases healthcare utilization—how often those who need medical attention receive it—during the first year of coverage (Baicker and Finkelstein 2011). Baicker and Finkelstein found that health insurance coverage increases the utilization of outpatient care by 35%, increases the utilization of prescription drugs by 15%, and increases overall hospital admissions

[2] For more information on the seminal research of the academics involved in the OHIE, see http://www.nber.org/oregon/6.publications.html and http://www.nber.org/oregon/4.data.html.

by 30% (Baicker and Finkelstein 2011). In the first 15 months, emergency department visits also increased by 40% (Finkelstein et al. 2013). Further, access to insurance increases the use of preventive care; for example, mammogram utilization increased 60% and cholesterol monitoring increased 20% (Baicker and Finkelstein 2011). Not only did insurance coverage increase utilization, the researchers also found that it improved stability when accessing primary care: 70% were more likely to have a regular place of care and 55% were more likely to have a primary care doctor (Baicker and Finkelstein 2011).

In addition, insurance coverage improved self-reported health. Access to health insurance increased the probability that people reported good health by 25% and decreased the probability of a decline in self-reported health by 40% (Finkelstein et al. 2013). Insured individuals were 25% less likely to be diagnosed as depressed (Baicker and Finkelstein 2011).

Overall, access to health insurance through the OHP improved financial stability in all aspects of enrollees' lives (Baicker and Finkelstein 2011). Importantly, it reduced the probability that people had to borrow money or skip payments on any bill to pay for their health expenses (Baicker and Finkelstein 2011). Further, the probability that enrollees had unpaid medical bills sent to a collection agency decreased by 25% (Baicker and Finkelstein 2011).

To arrive at these results, the researchers used the following reduced form equation to estimate the average difference in outcomes of interest between those who were selected in the lottery—those who gained access to sign up for the OHP—and those who were not selected in the lottery (Finkelstein et al. 2010):

$$\gamma_{\mathrm{ihj}} = \beta_0 + \beta_1 \mathrm{Lottery}_{\mathrm{h}} + \beta_2 \mathrm{X}_{\mathrm{ih}} + \beta_3 \mathrm{V}_{\mathrm{ih}} + \varepsilon_{ij} \tag{1}$$

However, it is more pertinent to isolate the effect of enrolling in OHP insurance—i.e. submitting an approved application—on these outcomes. This is an important distinction because being selected in the lottery did *not* mean that an individual was guaranteed to have received insurance. Some lottery winners chose not to apply, and others completed an application that was denied based on eligibility requirements. Therefore, to determine the causal effect of gaining health insurance on selected outcomes, the independent variable of interest is "Insurance" such that insurance measures actual enrollment in the OHP. This equation is:

$$\gamma_{\mathrm{ihj}} = \pi_0 + \pi_1 \mathrm{Insurance}_{\mathrm{ih}} + \pi_2 \mathrm{X}_{\mathrm{ih}} + \pi_3 \mathrm{V}_{\mathrm{ih}} + \nu_{ij} \tag{2}$$

To estimate equation (2), the two stage least squares (2SLS) equation, Finkelstein et al. used the below first stage equation with the variable "Lottery" as an instrument variable serving as a proxy for "Insurance" (Finkelstein et al. 2010):

$$Insurance_{\mathrm{ihj}} = \delta_0 + \delta_1 \mathrm{Lottery}_{\mathrm{ih}} + \delta_2 \mathrm{X}_{\mathrm{ih}} + \delta_3 \mathrm{V}_{\mathrm{ih}} + \mu_{ij} \tag{3}$$

In this framework, Finkelstein et al. assume that the population of those selected in the lottery closely matches those who apply to the OHP and meet eligibility requirements to enroll (Finkelstein et al. 2010). This thesis challenges the assumption that these groups are homogenous focusing on the low take-up rates of people eligible for social benefit programs across specific groups, as outlined in the literature review.

Literature Review

Barriers to Policy Take-up

Social safety-net programs in the U.S. have traditionally had low rates of participation because enrollment is not automatic; therefore, an individual must sign up and be approved to gain benefits (Allen et al. 2010). Failing to enroll in subsidized health insurance without another source of insurance seems irrational; however, it is estimated that only 50% of eligible and uninsured adults are enrolled in Medicaid (Allen et al. 2010). The current literature recognizes many barriers to the take-up of social programs: stigma due to receiving social program benefits, application barriers including completing paperwork and providing documentation (commonly referred to as transaction costs), lack of information about the program and/or eligibility requirements, and the individual tradeoffs associated with the magnitude of program benefits relative to costs (Currie 2006; Remler and Glied 2003). For example, Currie finds that enrollment in Medicaid increases as family size increases, concluding that program benefits (health insurance coverage, reduced financial burden, etc.) increase relative to constant costs (completing the application and providing documentation, facing stigma, etc.), thus making enrollment more attractive (Currie 2000).

Information and transaction costs are the most widely recognized barriers to policy take-up because it is inherently difficult to measure either an individual’s cost and benefit analysis or the role of stigma in decision-making. However, Stuber et al. find evidence to support that stigma is a barrier, reporting that 50% of respondents perceived at least one stigma-related problem in conjunction with enrollment or participation in Medicaid (Stuber et al. 2000).[3]

OHP take-up was expected to be higher than other social benefit programs for two reasons (Allen et al. 2010; Currie 2006). One reason was that those on the waiting list already expressed interest in gaining health insurance coverage, and the only way to get coverage was through selection in the lottery (and submitting an approved application); therefore, the population had already signaled that they wanted to enroll (Allen et al. 2010; Finkelstein et al. 2010). Furthermore, the 45-day window to apply to the OHP after lottery selection should mitigate time-inconsistent preferences—that is, those who forgo enrolling now even though they would get a later benefit from insurance coverage when a medical emergency occurs (Allen et al. 2010; Currie 2006). Thus, the short application window should encourage this self-selected group of people to sign up for coverage immediately without waiting until they need to utilize healthcare services.

Although the OHP take-up rate reached 61%, exceeding the 50% Medicaid take-up rate at the federal level, the program still had imperfect take-up. The sections below synthesize literature focused on identifying characteristics of populations that have lower take-up rates of social benefit programs, ending with an outline of methods for improving policy take-up.

[3] Respondents were asked to agree or disagree with the following assertions: Medicaid makes people like me lazy, people on Medicaid do not want others to know, people do not respect a person on Medicaid, the application process for Medicaid is humiliating, people are treated poorly when they apply for Medicaid, I have to answer unfair questions about my personal life, the rules of Medicaid take away personal freedoms, doctors do not provide quality care to people on Medicaid, doctors do not treat people with Medicaid equal to people with private health insurance (Stuber et al. 2000).

Evidence from the Oregon Health Insurance Experiment

In a follow-up survey, respondents who did not submit an application to the OHP although they were selected in the lottery were asked to explain why by selecting all of the choices that applied to them: I have not finished it yet, I decided not to apply, my income or assets were too high, I found other health insurance, the paperwork is a hassle, I could not find my paperwork to prove citizenship, I could not find other required paperwork, or other. Of the survey respondents, 33% said their paperwork was missing or incomplete, 23% said they thought their income or assets were too high to be eligible, 16% found alternative health insurance, and 33% indicated other (Allen et al. 2010). Of those who applied to OHP but were denied enrollment, 34% had an incomplete application while 63% were ineligible (55% had assets too high and 8% had alternative insurance) (Allen et al. 2010). Therefore, providing documentation and completing paperwork were clearly strong barriers to applying to the OHP. Given the concern about the dissemination of eligibility information and the burden of documentation, this thesis contends that these barriers impact individuals systematically across demographic categories.

Evidence from Medicaid and Related Programs

DeVoe et al. analyzed the participation of eligible children in the OHP Plus, the related OHP program. They compared children in the Supplemental Nutrition Assistance Program (SNAP) with those eligible for the OHP Plus and found that 23% of children in the former program were not enrolled in the latter, despite similar eligibility requirements (DeVoe et al. 2011). Specifically, they found that racial and ethnic minority status and higher household incomes correlated with higher odds of not being enrolled in OHP Plus when eligible (DeVoe et al. 2011). Similarly, from a population of 30,000 elderly individuals not enrolled in, but likely eligible for, the SNAP, Finkelstein and Notowidigdo find that the average enrollee is more likely to be White and a native English speaker (Finkelstein and Notowidigdo 2017). Therefore, this thesis will assess the likelihood that people apply to the OHP across racial and ethnic identifications, language spoken, and household income categories.

Currie found that eligible immigrant children are less likely to enroll in Medicaid, while Stuber et al., studying the role of stigma, found that 63% of low-income families think that immigrants are afraid to apply for Medicaid (Currie 2000; Stuber et al. 2000). They also found that Hispanic respondents—who were three times more likely to be eligible for but not enrolled in Medicaid compared to White respondents—commonly cited immigrant fears, lack of translators, and lack of knowledge on how to apply as barriers to signing up for Medicaid (Stuber et al. 2000).

Doty et al. found similar results regarding information and language barriers for Hispanics in the context of the Medicaid expansion under the Affordable Care Act (ACA). They found that at the end of the Affordable Care Act's first enrollment period at the inception of the program, 30% of Spanish-speaking Hispanics remained uninsured, while only 19% of English-speaking Hispanics were uninsured (Doty et al. 2014). Furthermore, only 50% of eligible Hispanic people were aware of the insurance marketplace created under the ACA, compared to 74% of White people, consistent with information barriers (Doty et al. 2014). This thesis will assess traits common among immigrant respondents, non-English language speakers, and non-White racial and ethnic identification (specifically Hispanic identification), as indicators for differential policy take-up rates.

In addition, Stuber et al. reported that 35% of respondents indicated that finding transportation was a problem when enrolling in Medicaid (Stuber et al. 2000). To capture transportation barriers, this thesis uses a variable indicating when a residence is in a metropolitan statistical area with the assumption that living in an urban center lessens transportation costs. Currie's research on immigrant children found evidence to support that enrollment in Medicaid increases as family size increases; therefore, this thesis will also test if household size or the number of people an individual signed up on the waiting list for coverage affects take-up rates.

Methods to Overcome Low Policy Take-Up

Although low policy take-up across social safety-net programs continues to be a concern globally, policymakers have not focused on how to devise policies that encourage higher participation from those eligible but not enrolled. Aizer analyzed the causes of low Medicaid take-up on a population in California from 1996 to 2000. She found that community-based application assistants who were trained to complete Medicaid applications were helpful tools to increase enrollment, and half of the applicants utilized this assistance (Aizer 2003). Additionally, bilingual application assistance increased enrollment among Hispanic and Asian families who had greater language barriers and immigration concerns (Aizer 2003). Widespread advertising and campaign efforts in a person's native language increased enrollment but had a less substantive effect than application assistance (Aizer 2003; Aizer 2007).

Finkelstein and Notowidigdo studied 30,000 elderly individuals not enrolled in the SNAP but who were likely eligible. The control group was not given any information about SNAP benefits and eligibility requirements, another group was given eligibility and benefit information, and the last group was given both information and application assistance. They found that 6% of the control group enrolled in SNAP over 9 months, compared to 11% of the information only group and 18% of the information and assistance group (Finkelstein and Notowidigdo 2017). Like Aizer, they found that increasing access to information increases enrollment, but application assistance is more effective than information campaigns alone (Finkelstein and Notowidigdo 2017).

While informational interventions are helpful, Manoli and Turner found that they have limited benefits beyond the first intervention point (Manoli and Turner 2014). They studied the Earned Income Tax Credit (EITC), finding that notices from the U.S. Internal Revenue Service to those who did not claim the EITC on their tax returns urge up to 80% of taxpayers to claim the credit in the same tax year (Manoli and Turner 2014). However, these effects retreat in the long-run because only 22% of those eligible people claim the tax credit one year after the notice was sent (Manoli and Turner 2014).

Currie summarizes that take-up rates across social benefit programs can be improved by automatic enrollment into the program and by removing all administrative barriers to enrollment (Currie 2006). Evidence suggests that removing only specific administrative barriers does not significantly increase take-up (Currie 2006). Similarly, Bansak and Raphael studied the State Children's Health Insurance Program and found that the combination of eliminating asset tests for eligibility, allowing for continuous coverage (i.e. removing renewal processes), and extending benefits to parents of eligible children increased take-up of the program (Bansak and Raphael 2007). More evidence from a case study in Wisconsin finds that shifting the administrative burden of enrolling in Medicaid from the individual to the state increases policy take-up (Herd et al. 2013). Overall, this thesis underscores the importance of designing social benefit programs with the understanding of how groups of people can be left out of the enrollment process.

Data and Methods

Data Collection and Survey Methods

The OHIE Researchers collected variables from both administrative data[4] and survey data to explore the outcomes from gaining health insurance coverage. Administrative data includes self-reported demographic characteristics,[5] Medicaid application and enrollment data, hospital discharge data, credit report data, and mortality data. The researchers also conducted mail surveys during the launch of the program, six months following the program, and a year following the program for all individuals on the waiting list regardless of selection in the lottery. Responding to each survey was voluntary for both OHP participants and those not selected for the program.

The surveys had a combined initial response rate of 36% (Finkelstein et al. 2010). For those who did not respond to survey attempts, the researchers followed up via mail and phone outreach, which elevated the total response rate to 50% (Finkelstein et al. 2010). There were 58,405 people included in the initial mail survey sent between June 2008 and January 2009, and 26,423 responded. In the sixth-month survey sample, a subsample of the initial survey population was sampled: 11,756 were sampled and 6,359 responded. The twelve-month survey was conducted on the entire sample of 58,405 people, and 23,777 responded.

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[4] Administrative data was gathered from the Human Services' Division of Medical Assistance Programs (DMAP), Oregon's Office of Health Policy and Research (OHPR), Oregon's Department of Human Services, Child and Families (CAF), and the Oregon Association of Hospitals and Health Systems (OAHHS), among others.

[5] Self-reported demographic characteristics include: year of birth, sex, if English is their preferred language for receiving materials, whether the individual signed themselves up for the lottery or was signed up by a household member, the number of household members included when signing up for the waiting list, if the individual gave their address as a P.O. box, if the zip code they gave is within a census-defined metropolitan statistical area, and if they provided a phone number (Finkelstein et al. 2010).

Survey questions aimed to assess respondents' feelings toward their health and financial situations and to collect additional demographic information. The three surveys sent out included the same questions; however, respondents were asked to re-assess their situation over the past six months. Respondents were asked to report their insurance status, healthcare costs, health status, and utilization of healthcare resources such as prescription drugs, dental care, doctor or clinic visits, and emergency room visits. Respondents were also asked to report demographic information such as employment status and hours worked, household income, race/ethnicity, educational attainment, and living arrangements.

This thesis utilizes publicly available data courtesy of the National Bureau of Economic Research and the OHIE.[6] Specifically, it utilizes the "oregonhie_descriptive_vars" dataset which includes information from the initial document that respondents filled out to sign up for the reservation list along with their lottery selection status and application status.[7] In addition, this thesis uses the "oregonhie_survey0m_vars" dataset with information about respondents collected from the initial survey.[8] Only the initial survey responses were used in this study in effort to control for respondents' health status and insurance history near the time they contemplated applying to the OHP. Each successive survey asked respondents to report their health and insurance status during the past six months only; therefore, responses

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[6] See here for the public use data: http://www.nber.org/oregon/4.data.html.

[7] Variables from this dataset include: applied_app, draw_lottery, numhh_list, age, have_phone, English_list, female_list, pobox_list, self_list, and zip_msa_list.

[8] Variables from this dataset includes: employ_det, employ_hrs, hhinc_cat, race_hisp, race_black, race_amerindian, race_asian, race_white, race_pacific, race_other, edu, hhsize, hhinc_pctfpl, need_med, need_rx, need_dent, doc_any, er_any, hosp_any, health_gen, ins_ohp, ins_medicare, ins_employer, ins_privpay, ins_othcov, ins_noins, and ins_months.

are not comparable throughout the three survey attempts, and only the initial survey is indicative of a person's eligibility for the OHP during the time they signed up.

Any observations from respondents who were not selected in the lottery to apply to the OHP (as indicated in the dataset by a treatment variable equal to 0) will be excluded. Further, a small amount of the total population of the study died following their lottery notification decision, so they will be excluded from this study because they might not have had the ability to apply for the OHP. The population for this study totals 8,661 after accounting for deaths, outlier observations, and any non-respondents to the initial survey attempt.

Regression Analysis

The above literature review contends that eligible groups of people face systematic barriers to enrollment in social safety-net programs. Therefore, this thesis questions prior OHIE results that were obtained from a study designed to assume that the group of people randomly selected in the lottery for health insurance access is comparable to those who apply to the OHP. The purpose of this study is to examine the likelihood that an individual selected via the lottery system applied to the OHP across demographic variables such as racial and ethnic identification, gender, income strata, educational attainment, employment status, age, household size, and geography. The thesis aims to identify characteristics and demographic traits that significantly affected a person's propensity to apply to the health insurance program.

To analyze the data, this study uses both a Linear Probability Model and a Logistic Regression Model and tests the resulting coefficients at the 1%, 5%, and 10% significance levels. Both models are used in conjunction with a binary dependent variable. In this case, the dependent variable, **applied_app**, is equal to 1 if the lottery winner applied to the OHP or 0 if they did not. The Linear Probability Model expresses a probability between 0 and 1 that a person applied to the Oregon Health Plan. Equation (4) and the condensed Equation (5) follow.[9]

$$\text{Applied App}_i = \beta_0 + \beta_1 \text{Draw Lottery}_i + \beta_2 \text{Age}_i + \beta_3 \text{English List}_i + \beta_4 \text{Female List}_i + \beta_5 \text{Race Amerindian}_i + \beta_6 \text{Race Asian}_i + \beta_7 \text{Race Black}_i + \beta_8 \text{Race Hisp}_i + \beta_9 \text{Race Other}_i + \beta_{10} \text{Race Pacific}_i + \beta_{11} \text{Have Phone List}_i + \beta_{12} \text{PObox List}_i + \beta_{13} \text{Zip MSA List}_i + \beta_{14} \text{Edu}_i + \beta_{15} \text{Employ Det}_i + \beta_{16} \text{Employ Hrs}_i + \beta_{17} \text{Hhinc Cat}_i + \beta_{18} \text{Hhinc Pct FPL}_i + \beta_{19} \text{Hhsize}_i + \beta_{20} \text{Numhh List}_i + \beta_{21} \text{Self List}_i + \beta_{22} \text{Health}_i + \beta_{23} \text{Insurance History}_i + \varepsilon_i \quad (4)$$

$$\text{Applied App}_i = \beta_0 + \beta_1 \text{Draw Lottery}_i + \beta_2 \text{Age}_i + \beta_3 \text{English List}_i + \beta_4 \text{Female List}_i + \beta_5 \text{Not White}_i + \beta_6 \text{Have Phone List}_i + \beta_7 \text{PObox List}_i + \beta_8 \text{Zip MSA List}_i + \beta_9 \text{Edu}_i + \beta_{10} \text{Unemployed}_i + \beta_{11} \text{Full Time Work}_i + \beta_{12} \text{Part Time Work}_i + \beta_{13} \text{Between 15,001 and 30,000}_i + \beta_{14} \text{Over 30,001}_i + \beta_{15} \text{Hhinc Pct FPL}_i + \beta_{16} \text{Hhsize}_i + \beta_{17} \text{Signed Up Additional People}_i + \beta_{18} \text{Self List}_i + \beta_{19} \text{Health}_i + \beta_{20} \text{Insurance History}_i + \varepsilon_i \quad (5)$$

However, the Linear Probability Model violates the Ordinary Least Squares (OLS) assumptions of heteroscedasticity, linearity, and normally-distributed error terms. Therefore, this study also uses a Logistic Regression Model, a non-linear model where probabilities are strictly bounded between 0 and 1 (a limitation of the Linear Probability Model is that probabilities can fall outside of these bounds). An advantage of the non-linear model is that the interpretation depends on the levels of the variable. Using the Logistic Regression Model, predicted values are calculated using the cumulative probability distribution function. Equation (6) and the condensed Equation (7) follow.

[9] Each variable is explained in depth in the next section entitled Regression Variables.

$$\ln\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 \text{Draw Lottery}_i + \beta_2 \text{Age}_i + \beta_3 \text{English List}_i + \beta_4 \text{Female List}_i + \beta_5 \text{Race Amerindian}_i + \beta_6 \text{Race Asian}_i + \beta_7 \text{Race Black}_i + \beta_8 \text{Race Hisp}_i + \beta_9 \text{Race Other}_i + \beta_{10} \text{Race Pacific}_i + \beta_{11} \text{Have Phone List}_i + \beta_{12} \text{PObox List}_i + \beta_{13} \text{Zip MSA List}_i + \beta_{14} \text{Edu}_i + \beta_{15} \text{Employ Det}_i + \beta_{16} \text{Employ Hrs}_i + \beta_{17} \text{Hhinc Cat}_i + \beta_{18} \text{Hhinc Pct FPL}_i + \beta_{19} \text{Hhsize}_i + \beta_{20} \text{Numhh List}_i + \beta_{21} \text{Self List}_i + \beta_{22} \text{Health}_i + \beta_{23} \text{Insurance History}_i + \varepsilon_i \tag{6}$$

$$\ln\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 \text{Draw Lottery}_i + \beta_2 \text{Age}_i + \beta_3 \text{English List}_i + \beta_4 \text{Female List}_i + \beta_5 \text{Not White}_i + \beta_6 \text{Have Phone List}_i + \beta_7 \text{PObox List}_i + \beta_8 \text{Zip MSA List}_i + \beta_9 \text{Edu}_i + \beta_{10} \text{Unemployed}_i + \beta_{11} \text{Full Time Work}_i + \beta_{12} \text{Part Time Work}_i + \beta_{13} \text{Between 15,001 and 30,000}_i + \beta_{14} \text{Over 30,001}_i + \beta_{15} \text{Hhinc Pct FPL}_i + \beta_{16} \text{Hhsize}_i + \beta_{17} \text{Signed Up Additional People}_i + \beta_{18} \text{Self List}_i + \beta_{19} \text{Health}_i + \beta_{20} \text{Insurance History}_i + \varepsilon_i \tag{7}$$

P is the probability that the lottery winner submitted an application to the OHP, and is calculated using $P = \frac{e^{(\beta_0+\beta_1 X_1+\cdots+\beta_{23} X_{23})}}{1+e^{(\beta_0+\beta_1 X_1+\cdots+\beta_{23} X_{23})}}$. With both models, I will utilize robust standard errors to combat heteroscedasticity.

Regression Variables

The following discussion details each variable used in Equations (4) through (7). Due to small sample sizes in select categories, this thesis combines dummy variable categories where appropriate.[10] See Appendix 2 for a key explaining the expanded and condensed equation variables.

Treatment Variables

Individuals in the study are identified using a random person identifier, **person_id**, which is constant across all the datasets in the OHIE. The dependent variable examined in this study is **applied_app**, which is a dummy variable equal to 1 if

[10] See Appendix 1.

the person applied to the OHP and 0 if they did not. Only those who were in the **treatment** group (treatment = 1) were selected in the lottery to be eligible to apply to the OHP. The **draw_lottery** variable indicates the eight lottery selections between March and September of 2008. The categorical variable equals 1 if the respondent was selected on the first draw or 8 if they were selected on the eighth draw.[11]

Demographic Variables

To determine if the propensity to apply for the OHP changes among racial and ethnic identification, dummy variables were included equal to 1 if respondents identified with the race or ethnicity in question and 0 if they did not. Options include: White (**race_white**), Spanish, Hispanic, or Latino (**race_hisp**), Black or African-American (**race_black**), American Indian or Alaska Native (**race_amerindian**), Asian (**race_asian**), Native Hawaiian or Pacific Islander (**race_pacific**), or another race (**race_other_qn**). Respondents were asked to select all races that applied to them. In the condensed equations, the variable **Not White** includes any person who does not identify as White.

In addition, the variable **English_list** indicates that the individual requested English-language materials instead of requesting materials in another language. Other demographic variables include gender and age. The dummy variable **female_list** is equal to 1 if the person is a female or equal to 0 if the person is a male. **Age** was generated from the continuous variable **birthyear_list** which codes for the birth year of the respondent.

[11] The dates of the lottery draws in order are: March 5, 2008, March 27, 2008, April 8, 2008, May 1, 2008, June 2, 2008, July 1, 2008, August 1, 2008, and September 2, 2008.

Geographic Location Variables

To capture urbanicity, the variable **zip_msa_list** was included which is a dummy variable equal to 1 if the individual's zip code indicated a residence in a census-defined metropolitan statistical area (MSA) and 0 if not. The variable **have_phone_list** indicated that the person gave a phone number. If the respondent gave an address that was a P.O. Box, the variable **pobox_list** would equal 1 and 0 if otherwise.

Education and Employment Variables

Employment characteristics were captured in the categorical variable **employ_det** which equals 1 if the person was employed, 2 if the person was self-employed, 3 if the person was not employed, or 4 if the person was retired. In the condensed equation, both self-employed and employed categories were classified as **employed**, whereas unemployed and retired categories were classified as **unemployed**. Full-time versus part-time work was captured in **employ_hrs,** a categorical variable equal to 1 if they did not work, 2 if they worked less than 20 hours a week, 3 if they worked between 20 and 29 hours a week, and 4 if they worked over 30 hours a week. Accordingly, those who worked less than 29 hours a week were classified under **part time work** while those who worked more were classified under **full time work**. Educational attainment was captured through the variable **edu**, which was a categorical variable equal to 1 if the respondent did not graduate high school, 2 if they had a high school diploma or the equivalent, 3 if they had a vocational or 2-year college degree, or 4 if they had a 4-year degree.

Household Income and Size Variables

Household income was measured with two variables. Household income category, **hhinc_cat**, captures the gross household income prior to taxes and deductions. The categorical variable assumes ascending values from 1 to 22 with the variable equal to 1 if the gross household income was $0 and 22 if the gross household income was above $50,000. The variable **below 15,000** captures gross household income categories from $0-$15,000 whereas **between 15,001 and 30,000** captures income categories from $15,001 to $30,000. Incomes over $30,001 are captured by the variable **over 30,001**. Furthermore, **hhinc_pctfpl** is a continuous variable that captures household income as a percent of the federal poverty line.

In addition, **numhh_list** represents the number of people in the household on the waiting list. If the value equals 1, the person only signed up himself or herself. If the value is 2 or 3, it indicates the person signed up one or two additional people. In the condensed equation, those who signed up more than one person were grouped in the variable **signed up additional people**. In addition, the variable **self_list** is a dummy variable that equals 1 if the person signed themselves up for the OHP and 0 if they did not. Household size, **hhsize**, is a continuous variable that measures how many family members (both adults and children) were living at the respondent's residence.

Health Status and Health Insurance History Variables

This thesis controls for the health status of survey respondents, acknowledging that those who are less healthy would have a greater incentive to apply to the OHP. Variables to control for health include: if the person needed medical care in the last six months (**need_med**), if the person needed prescription medicine in the last six months (**need_rx**), if the person needed dental care within this time frame (**need_dent**), if the person had any primary care visits within the last six months (**doc_any**), if the person had any Emergency Room visits (**er_any**), and if the person had any hospital visits (**hosp_any**). In addition, respondents were asked to rate their overall health as excellent, very good, good, fair, or poor which is captured in the variable **health_gen**.

Controlling for a respondent's insurance history is also important because OHP eligibility requirements state that applicants must be ineligible for Medicaid and/or Medicare and must be uninsured for the past six months. Therefore, respondents were asked if they had any health insurance through Medicaid (**ins_ohp**), Medicare (**ins_medicare**), an employer (**ins_employer**), a private plan (**ins_privpay**), other coverage (**ins_othcov**), or no insurance (**ins_noins**). This thesis also includes a variable, **ins_months**, indicating how many months of the last six that a person had health insurance coverage.

Results

This thesis scrutinizes past OHIE studies that used an instrument variable regression that assumed that people selected in the lottery matched the population who enrolled in OHP insurance. This thesis contends that these groups are heterogeneous, hypothesizing that take-up rates vary across demographic characteristics. Overall, this thesis finds statistically significant evidence to support the hypothesis that the groups are heterogeneous in the categories outlined below.[12]

Demographic Variables

Those who identify as Asian are between 4.9 and 5.3 percentage points (depending on whether the Linear Probability Model or the Logistic Regression Model is used) more likely to apply to the OHP compared to those who identify as White, with all other factors remaining equal. Additionally, individuals who identify as Native Hawaiian or Pacific Islander are 10.9 percentage points less likely to apply compared to White individuals. No other racial or ethnic identification categories were significant at the 10% level; however, the coefficient on Black had a low P-value, thus warranting attention. Individuals who identify as Black are 4.1 percentage points less likely to apply compared to White individuals. Gender was also an important indicator of the likelihood that a person applied to the OHP. This study finds that women are less likely than men to apply by between 1.6 and 2.1 percentage points. Moreover, as age increases by one year, the probability that a person applies to the OHP increases by 0.2 percentage points.

[12] Reference Table 1 and Table 2 for regression outputs.

Geographic Location Variables

Having a phone increases the probability that a person applies to the OHP by between 4.8 and 5.5 percentage points compared to individuals who did not have a phone. Additionally, individuals who listed a P.O. Box as their address are more likely to apply to the OHP by 2.4 percentage points compared to those who did not.

Education and Employment Variables

Self-employed individuals are more likely to apply to the OHP by between 2.7 and 2.9 percentage points compared to those who are employed, but not self-employed. Retirees are less likely to apply by between 13.4 and 15.5 percentage points compared to those who are employed. Moreover, a person working more than 30+ hours per week is less likely to apply by between 10.7 and 12.2 percentage points compared to those who do not work. Educational attainment also changes the propensity to apply, as individuals with a high school diploma or GED are less likely than high school dropouts to apply by between 2.9 and 3.1 percentage points.

Household Income and Size Variables

As household income as a percent of the federal poverty line increases by 1 percentage point, the probability a person applies to the OHP decreases by 0.1 percentage points. Furthermore, a person who signed up at least one additional person on the waiting list was more likely to apply by a magnitude between 2.2 and 2.5 percentage points, compared to someone who signed himself or herself up. Those who signed themselves up were more likely to apply to the OHP by between 7.2 and 9.1 percentage points compared to those who were signed up by someone else. In addition, an increase in one family member (adult or child) living in a person's home lowered the likelihood that they applied by 0.6 percentage points.

Table 1: The Effect of Demographic Variables on the Probability of Applying to the OHP using the Linear Probability Model Regression[13]

Variable of Interest	Coefficient (Percentage Points)	Robust Standard Error	P-Value
Demographic Variables			
Age	0.228	0.000	0.000***
English Speaker	-2.762	0.022	0.200
Female	-1.596	0.009	0.090*
Not White	-1.635	0.014	0.247
Geographic Location Variables			
Gave Phone Number	5.534	0.015	0.000***
Gave P.O. Box as an Address	2.451	0.014	0.074*
Zip Code is a MSA	1.353	0.011	0.208
Education & Employment Variables			
Highest Level of Education Completed			
High School Diploma or GED	-2.898	0.013	0.023**
Vocational or 2-Year Degree	-1.709	0.015	0.258
4-Year Degree	-1.306	0.019	0.489
Employment Status			
Unemployed	-5.943	0.053	0.265
Average Hours Worked/Week			
Full Time Work	-11.002	0.054	0.041**
Part Time Work	-3.292	0.054	0.541
Household Income and Size Variables			
Household Income Category			
Between 15,001 and 30,000	2.156	0.015	0.164
Over 30,001	-0.482	0.030	0.871
Household Income as % of FPL	-0.045	0.000	0.001***
Household Size (Adults and Children)	-0.574	0.003	0.069*
Number of People in Household on List			
Signed Up Additional People	2.533	0.012	0.036**
Signed Him or Herself up on List	9.097	0.016	0.000***

Variable of Interest	Coefficient (Percentage Points)	Robust Standard Error	P-Value
Demographic Variables			
Age	0.238	0.000	0.000***
English Speaker	-1.348	0.023	0.562
Female	-1.911	0.009	0.042**
American Indian/Alaska Native	-0.131	0.019	0.946
Asian	5.264	0.026	0.040**
Black	-4.064	0.026	0.121
Hispanic, Spanish, Latino	-1.345	0.021	0.520
Other Race	-0.544	0.022	0.801
Native Hawaiian/Pacific Islander	-10.878	0.057	0.056*
Geographic Location Variables			
Gave Phone Number	5.636	0.015	0.000***
Gave P.O. Box as an Address	2.356	0.014	0.086*
Zip Code is a MSA	1.309	0.011	0.221
Education & Employment Variables			
Highest Level of Education Completed			
High School Diploma or GED	-2.956	0.013	0.021**
Vocational or 2-Year Degree	-1.850	0.015	0.223
4-Year Degree	-1.522	0.019	0.419
Employment Status			
Self-Employed	2.916	0.016	0.068*
Not Employed	-4.189	0.055	0.444
Retired	-13.350	0.062	0.030**
Average Hours Worked/Week			
<20 hrs/week	-4.300	0.056	0.439
20-29 hrs/week	-1.564	0.055	0.778
30+ hrs/week	-10.715	0.055	0.049**

[13] *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Variable of Interest	Coefficient (Percentage Points)	Robust Standard Error	P-Value
Household Income and Size Variables			
Household Income Category			
$1 - $2,500	-2.484	0.018	0.165
$2,501 - $5,000	-1.277	0.021	0.545
$5,001 - $7,500	-1.201	0.022	0.586
$7,501 - $10,000	0.315	0.023	0.891
$10,001 - $12,500	0.875	0.026	0.733
$12,501 - $15,000	4.077	0.028	0.149
$15,001 - $17,500	10.001	0.031	0.001***
$17,501 - $20,000	4.492	0.034	0.188
$20,001 - $22,500	-0.692	0.039	0.858
$22,501 - $25,000	0.653	0.042	0.878
$25,001 - $27,500	1.641	0.047	0.727
$27,501 - $30,000	-0.543	0.050	0.913
$30,001 - $32,500	-0.032	0.056	0.995
$32,501 - $35,000	-4.090	0.062	0.511
$35,001 - $37,500	10.769	0.066	0.104
$37,501 - $40,000	-7.435	0.073	0.309
$40,001 - $42,500	-1.173	0.085	0.890
$42,501 - $45,000	-5.541	0.102	0.586
$45,001 - $47,500	12.877	0.095	0.174
$47,501 - $50,000	8.508	0.093	0.358
>$50,000	6.172	0.079	0.432
Household Income as % of FPL	-0.056	0.000	0.017**
Household Size (Adults and Children)	-0.712	0.004	0.060*
Number of People in Household on List			
Signed Self Up + 1 Additional Person	2.478	0.012	0.042**
Signed Self Up + 2 Additional People	4.832	0.080	0.547
Signed Him or Herself up on List	9.015	0.016	0.000***

Table 2: The Effect of Demographic Variables on the Probability of Applying to the OHP using the Logistic Model Regression

Variable of Interest	Coefficient (Percentage Points)	Delta-Method Standard Error	P-Value
Demographic Variables			
Age	0.234	0.000	0.000***
English Speaker	-2.434	0.022	0.261
Female	-1.701	0.009	0.073*
Not White	-1.504	0.014	0.272
Geographic Location Variables			
Gave Phone Number	5.298	0.014	0.000***
Gave P.O. Box as an Address	2.665	0.015	0.069*
Zip Code is a MSA	1.451	0.011	0.176
Education & Employment Variables			
Highest Level of Education Completed			
High School Diploma or GED	-2.884	0.013	0.026**
Vocational or 2-Year Degree	-1.736	0.015	0.255
4-Year Degree	-1.238	0.019	0.504
Employment Status			
Unemployed	-6.360	0.061	0.299
Average Hours Worked/Week			
Full Time Work	-11.149	0.061	0.070*
Part Time Work	-3.547	0.062	0.567
Household Income and Size Variables			
Household Income Category			
Between 15,001 and 30,000	2.215	0.015	0.135
Over 30,001	0.474	0.027	0.862
Household Income as % of FPL	-0.046	0.000	0.000***
Household Size (Adults and Children)	-0.637	0.003	0.045**
Number of People in Household on List			
Signed Up Additional People	2.484	0.012	0.047**
Signed Him or Herself up on List	8.576	0.015	0.000***

Variable of Interest	Coefficient (Percentage Points)	Delta-Method Standard Error	P-Value
Demographic Variables			
Age	0.244	0.000	0.000***
English Speaker	-1.103	0.023	0.637
Female	-2.006	0.009	0.034**
American Indian/Alaska Native	-0.126	0.019	0.948
Asian	5.464	0.027	0.046**
Black	-3.915	0.024	0.106
Hispanic, Spanish, Latino	-1.214	0.020	0.549
Other Race	-0.517	0.021	0.805
Native Hawaiian/Pacific Islander	-9.608	0.048	0.043**
Geographic Location Variables			
Gave Phone Number	5.383	0.014	0.000***
Gave P.O. Box as an Address	2.559	0.015	0.079*
Zip Code is a MSA	1.386	0.011	0.194
Education & Employment Variables			
Highest Level of Education Completed			
High School Diploma or GED	-2.924	0.013	0.025**
Vocational or 2-Year Degree	-1.914	0.015	0.213
4-Year Degree	-1.508	0.019	0.416
Employment Status			
Self-Employed	2.621	0.015	0.080*
Not Employed	-4.483	0.061	0.460
Retired	-14.271	0.071	0.043**
Average Hours Worked/Week			
<20 hrs/week	-4.497	0.061	0.465
20-29 hrs/week	-1.432	0.059	0.808
30+ hrs/week	-11.163	0.064	0.082*

Variable of Interest	Coefficient (Percentage Points)	Delta-Method Standard Error	P-Value
Household Income and Size Variables			
Household Income Category			
$1 - $2,500	-2.900	0.021	0.162
$2,501 - $5,000	-1.628	0.023	0.488
$5,001 - $7,500	-1.613	0.024	0.495
$7,501 - $10,000	-0.045	0.024	0.985
$10,001 - $12,500	0.393	0.025	0.878
$12,501 - $15,000	3.403	0.027	0.210
$15,001 - $17,500	8.873	0.029	0.002***
$17,501 - $20,000	3.856	0.031	0.219
$20,001 - $22,500	-0.836	0.036	0.818
$22,501 - $25,000	0.623	0.039	0.872
$25,001 - $27,500	1.592	0.043	0.709
$27,501 - $30,000	-0.331	0.045	0.942
$30,001 - $32,500	0.316	0.050	0.949
$32,501 - $35,000	-2.959	0.057	0.606
$35,001 - $37,500	9.131	0.052	0.077*
$37,501 - $40,000	-6.092	0.070	0.386
$40,001 - $42,500	-0.337	0.073	0.963
$42,501 - $45,000	-4.274	0.093	0.645
$45,001 - $47,500	10.624	0.067	0.115
$47,501 - $50,000	7.201	0.074	0.330
>$50,000	5.581	0.063	0.378
Household Income as % of FPL	-0.055	0.000	0.010***
Household Size (Adults and Children)	-0.762	0.004	0.040**
Number of People in Household on List			
Signed Self Up + 1 Additional Person	2.471	0.012	0.045**
Signed Self Up + 2 Additional People	4.115	0.072	0.565
Signed Him or Herself up on List	0.085	0.015	0.000***

Limitations

The design of this thesis inevitably has some limitations. It is important to recognize that the target population for the study—low-income uninsured Oregonians—does not accurately compare to the overall population of low-income uninsured people in the U.S. because Oregon has a lower African-American population (by 18 percentage points) and a lower Hispanic population (by 6 percentage points) than the U.S. as a whole (Allen et al. 2010). Overall, Oregon has a disproportionately small minority population; therefore, the data from this thesis reflects small sample sizes in racial minority categories. In the population of this study, only 17.8% of respondents indicated that they were not racially White. In an effort to derive evidence from limited sample sizes, minority categories were grouped together in a "non-white" category. Small sample sizes showed up in other variable categories such as employment status, with only 3.4% of respondents indicating that they were retired; therefore, these respondents were re-classified generally as unemployed. Only 0.2% of the population signed up themselves on the OHP waiting list along with two other people, so this population was re-classified as anyone who signed up additional people on the waiting list.[14] This thesis draws on the most granular data to interpret results where possible.

Another limitation of this thesis is that the population excludes any person who did not respond to the initial survey or who left a question on the survey unanswered. The initial application for the waiting list was designed to be brief to encourage

[14] See Appendix 1 for the frequency of responses for all categorical variables. See Appendix 2 for an entire breakdown of the re-classified categories used in the condensed equation.

participation; therefore, the study relies mostly on survey data.[15] This could bias estimates because a respondent to the survey may be more likely to apply to the OHP. In fact, 74% of the population of this study (N=8,661) applied to the OHP compared to just 61% of the entire treatment population (N=29,834) (See Appendix 1). One explanation is that individuals completed the survey because there was monetary incentive, and these may be the same people with the lowest incomes who would gain the most utility from OHP enrollment. Income level is held constant in the regressions, however, so this should not bias the coefficients. The coefficients may be biased to the extent that there are characteristics of the survey population that are not present in the general treatment population and are not controlled for in the regressions. The frequency of each categorical response to the variables observed across the entire treatment population were cross-checked against the smaller population used in this study.[16] This thesis finds that the frequency of these responses was roughly consistent across the two populations.

Another limitation is that individuals who thought they would meet OHP eligibility requirements may have signed up more often than those who were uncertain about meeting requirements. These requirements include: applicants must be between 19 and 64 years old, be residents of Oregon or legal immigrants, be ineligible for Medicaid and/or Medicare, be uninsured for the past six months, have an income below 100% of the federal poverty line, and have assets below $2,000. This thesis controls for

[15] Stuber et al. find that 36% of respondents agreed that the Medicaid application forced them to answer unfair questions about their personal life, so it was important to policymakers and researchers to make the initial document concise (Stuber et al. 2000).
[16] Variables include: applied_app, draw_lottery, numhh_list, age, have_phone, English_list, female_list, pobox_list, self_list, and zip_msa_list.

age, income, and health insurance history requirements; however, it is unable to control for residency or immigration status and maximum asset requirements. In addition, this thesis utilizes data for health status and insurance history from the initial survey which was sent out between June 2008 and January 2009, while selection into the lottery occurred between March and September of 2008. These proxies for initial health and coverage status could be misleading depending on when lottery winners who applied to the OHP gained coverage and when respondents mailed back their survey.

Conclusions and Policy Implications

The OHIE researchers' estimating equation uses the instrument variable "Lottery" as an indication of assignment into the treatment group. Therefore, "Lottery" is a proxy variable for actual treatment or enrollment of an individual on the OHP ("Insurance"). The researchers assume that their study population is comprised of almost all "compliers" (Finkelstein et al. 2010).[17] While "compliers" cannot be conclusively identified because only one state of the world is observed, the researchers define "approximate compliers" as individuals selected into the OHP and who enroll, and they define "approximate non-compliers" as individuals selected for but who did not enroll in the OHP (Finkelstein et al. 2010).[18] Although the researchers outlined what would constitute as "approximate non-compliers," they expected that non-compliance was random among individuals, so their estimating equations treated everyone as "compliers." However, results from this thesis find statistically significant evidence supporting non-random selection as a "non-complier;" therefore, the local average treatment effects (LATE) derived from OHIE studies should be examined with this evidence.

[17] "Compliers" are defined as individuals assigned to the treatment group who follow their treatment assignment. "Always takers" are individuals who are always treated, regardless of assignment into the treatment group. "Never takers" are individuals who never get treated, regardless of assignment into the treatment group. Lastly, "Non-compliers" do the opposite of their treatment assignment. Each individual will fall into one of these categories although definitive placement into a category is unknown because researchers cannot observe the behavior of individuals in the counterfactual situation. For example, if an individual in the treatment group complies with their treatment assignment, it is uncertain whether they are a "complier" or an "always taker" because one cannot observe their action if they were not in the treatment group.

[18] This is possible due to the design of the study where an individual was not able to enroll on the OHP Standard without lottery selection so there was no "always takers" (Finkelstein et al. 2010).

Said another way, this thesis shows that policy take-up rates were non-random across demographic characteristics. Specifically, these results underscore evidence from DeVoe et al., who find that racial and ethnic minority status leads to lower policy take-up rates (DeVoe et al. 2011). This study finds evidence that individuals who identify as Native Hawaiian/Pacific Islander or Black are less likely to apply to the OHP compared to their White counterparts. Further, the coefficients on each of the race variables, except Asian, were negative, although they were not all statistically significant. This study hence utilized Blinder-Oaxaca Decomposition to analyze the participation gap between Non-White individuals and White individuals, finding that 74% of White individuals applied versus 72% of minorities—a gap of 2%. Blinder-Oaxaca Decomposition is utilized to analyze the mean gap between two groups and quantify how much of the gap is driven by their characteristics, driven by their response differences (betas), or driven by their unobservable characteristics (Jann 2008). If Non-White individuals were given the same characteristics (such as educational attainment, household income, age, employment status, etc.) as White individuals, then the mean increase in the propensity to apply is 0.06 percentage points. Instead, if the beta coefficients on White are given to the Non-White population, then the mean increase in the propensity to apply is 2.00 percentage points—explaining the gap entirely. This is consistent with the interpretation that behavioral differences between Non-White and White individuals matter for take-up of the OHP.

Interestingly, individuals who identify as Asian had a higher likelihood of applying for the OHP once selected in the lottery than their White counterparts, which contradicts findings from Aizer, who shows that bilingual application assistance had the greatest effect on Asian families with immigration concerns and language barriers (Aizer 2003). Within the context of the OHP enrollment, enrollees did not have access to application assistance. Therefore, these results may indicate that the Asian-American communities in this study population have higher levels of knowledge about state resources and/or experience lower levels of stigma when applying for these resources, even if bilingual assistance is not available during the application process.

This study shows no statistically significant evidence that non-English speakers had different take-up rates compared to English speakers, which may indicate that the design of the OHIE study successfully provided materials in multiple languages to participants, thereby removing the language barrier. On the initial document to sign up for the waiting list, respondents were asked to indicate their preferred language for receiving written materials. This is an interesting result, however, because researchers such as Doty et al. and Finkelstein et al. have showed evidence supporting differential policy take-up rates between English-speakers and non-English speakers for social programs such as Medicaid and SNAP, respectively (Doty et al. 2014; Finkelstein and Notowidigdo 2017).

Age and gender also led to differential rates of policy take-up. Older people were more likely to apply to the OHP after being selected in the 2008 lottery. One would suspect that all else being equal, older individuals would be more likely to utilize healthcare services for preventive care measures or screenings and would benefit more from coverage. Women are less likely to apply to the OHP after lottery selection, which may be explained by a higher likelihood of taking on child-care responsibilities, thus imposing more time constraints on them compared to their male counterparts.

This thesis also looked at geography or transportation variables, finding that those who had a phone were more likely to apply to the OHP then those who did not. However, this may be a function of the survey outreach attempts, since the OHIE researchers followed up via phone call to anyone who did not respond to the survey, so individuals with a phone may have been oversampled in the population. Individuals indicating a P.O. Box as an address were also more likely to apply than those without one, possibly signaling either increased access to urban centers or an increased frequency of checking their mail. Both factors would increase the likelihood that an individual had timely information about the program and how to apply, since applications were sent via mail. There was no statistically significant difference in take-up rates between individuals living within a MSA and those living outside of a MSA. This could indicate that OHIE researchers took appropriate measures to make gathering information about the program and applying easy remotely. But, it is a surprising finding because Stuber et al. report that finding transportation was a widely-cited barrier to applying for Medicaid (Stuber et al. 2000).

This study supports the finding that take-up rates differed among educational attainment and employment categories of the individuals who were selected in the OHP lottery. Specifically, individuals with a high school diploma or GED had lower policy take-up rates than the equivalent high school dropout. This may signal that individuals with more education/skills are more confident about improving their current financial position through finding a better job or finding one that offers insurance benefits rather than the alternative of applying for state-sponsored health insurance. Employment classifications also mattered. A self-employed person applied to the OHP at higher rates than an employed person, while a retiree was much less likely to apply. Since most people access health insurance through an employer, a self-employed person may be more likely to secure insurance through the OHP knowing they will never have access to employer-sponsored insurance. Retirees were less likely to apply, possibly due to a shorter time horizon until they qualify for Medicare, resulting in less overall benefit compared to the costs of applying. Individuals who worked more than 30+ hours per week were meaningfully less likely to apply compared to those who did not work, likely due to time constraints posed by full-time (or near full-time) employment.

In the context of the Oregon Health Plan Plus (the related OHP program), DeVoe et al. find that individuals with higher household incomes had lower policy take-up (DeVoe et al. 2011). Accordingly, this thesis finds that as gross household income as a percent of the federal poverty line increases, an individual is less likely to apply to the OHP. Higher self-reported household income, especially around the threshold of income eligibility, may cause an individual not to apply in anticipation that their verifiable household income may not meet eligibility requirements. Household size also impacts take-up rates. While Currie finds that enrollment in Medicaid increases as family size increases for immigrant children, this study finds the opposite effect: an increase in household size decreases the probability of applying to the OHP (Currie 2000). However, results from this study are not directly comparable to Currie's because this study classifies household size as both children and adults living in the residence. An increase in household size may impose additional time constraints on an individual, making him/her less likely to apply as a result.

This thesis shows that individuals who signed themselves up and at least one additional person on the waiting list were more likely to apply than those who only signed themselves up. This can be explained because if one person from the household was chosen in the lottery, all people in the household were eligible to apply, thus the benefit of enrolling 2 or more people is greater relative to fixed costs. People who signed themselves up, relative to those who were signed up by a member of their household, were more likely to apply because they made a cognizant choice to be considered for enrollment.

Policymakers should aim to educate and support groups of people in the enrollment process who have lower take-up rates. Various researchers have already urged policymakers to implement application assistance, particularly targeted at racial and ethnic minorities with language barriers and immigration concerns (Aizer 2003). In addition, researchers have identified that advertising efforts in non-English languages promote network effects among communities that can increase knowledge about programs (Aizer 2007). Other research has shown that removing administrative barriers in the application process improves take-up rates across all individuals (Currie 2006; Bansak and Raphael 2007; Herd et al. 2013). Policymakers may choose to design policy to support disadvantaged groups, thereby mitigating differential policy take-up. On the other hand, removing administrative barriers, such as shortening and simplifying the application form, lowering the burden of documentation, and allowing for continuous coverage, are cheap and easy-to-implement changes to encourage widespread improvement in take-up. However, removing administrative barriers may allow ineligible people to access the program.

This thesis asks which groups of people are left out of the enrollment process of social benefit programs and provides evidence to support that take-up of the OHP is non-random across demographic variables. Within the literature on policy take-up, this thesis highlights new groups of people—particularly females, older individuals, individuals with higher educational attainment, retirees, full-time workers, and larger households—who are shown to experience lower take-up rates within the context of the OHP, but who have not been considered disadvantaged in other studies. Further studies on the topic are needed to conclusively identify the mechanisms that limit policy take-up in these groups of people.

Oregon policymakers may consider advertising efforts that not only target the low-income and uninsured population, but also target these specific demographics. Direct mailers to these groups of people, additional follow-up information and nudges, and application assistance may be considered. Oregon policymakers could also work with specialized advocacy groups to target these populations. For example, policymakers could distribute information and provide application assistance through Planned Parenthood to target low-income women. If further studies acknowledge that time constraints led to low take-up rates for females, as opposed to information lapses, than application assistance may be more helpful than information to reduce differential policy take-up. However, the uncertainty about which mechanisms are driving low policy take-up in these groups makes identifying policy recommendations difficult. In addition, identifying and following up with these populations may be costly and complex, so more work needs to be done to quantify the social welfare gains of targeted outreach attempts versus other alternatives to increase policy take-up generally.

Appendix 1 – Frequency of Categorical Variable Reponses

applied_app: Submitted an application to OHP		
Label	**Frequency**	**Percent**
Did not submit an application to OHP	2,280	26.3
Submitted an Application to OHP	6,381	73.7

edu: Highest level of education completed		
Label	**Frequency**	**Percent**
Less then high school	1,428	16.5
High school diploma or GED	4,479	51.7
Vocational or 2-year degree	1,832	21.2
4-year degree	922	10.6

employ_det: Currently employed or self-employed		
Label	**Frequency**	**Percent**
Employed	3,371	38.9
Self-employed	910	10.5
Not Employed	4,096	47.3
Retired	284	3.3

employ_hrs: Average hrs worked/week		
Label	**Frequency**	**Percent**
Do not currently work	4,427	51.1
Work <20 hrs/week	805	9.3
Work 20-29 hrs/week	922	10.6
Work 30+ hrs/week	2,507	28.9

english_list: Individual requested english-language materials		
Label	**Frequency**	**Percent**
Requested materials in another language	576	6.7
Requested English materials	8,085	93.3

female_list: Male or female		
Label	**Frequency**	**Percent**
Male	3,543	40.9
Female	5,118	59.1

have_phone_list: Gave phone number on lottery sign up		
Label	**Frequency**	**Percent**
Did not give phone number	981	11.3
Gave phone number	7,680	88.7

hhinc_cat: Household income category		
Label	Frequency	Percent
$0	1,072	12.4
$1 - $2,500	926	10.7
$2,501 - $5,000	627	7.2
$5,001 - $7,500	612	7.1
$7,501 - $10,000	718	8.3
$10,001 - $12,500	775	8.9
$12,501 - $15,000	710	8.2
$15,001 - $17,500	543	6.3
$17,501 - $20,000	598	6.9
$20,001 - $22,500	439	5.1
$22,501 - $25,000	393	4.5
$25,001 - $27,500	244	2.8
$27,501 - $30,000	269	3.1
$30,001 - $32,500	164	1.9
$32,501 - $35,000	126	1.5
$35,001 - $37,500	88	1.0
$37,501 - $40,000	87	1.0
$40,001 - $42,500	57	0.7
$42,501 - $45,000	29	0.3
$45,001 - $47,500	34	0.4
$47,501 - $50,000	38	0.4
>$50,000	112	1.3

numhh_list: Number of people in household on lottery list		
Label	Frequency	Percent
Signed self up	5,525	63.8
Signed self up + 1 additional person	3,117	36.0
Signed self up + 2 additional people	19	0.2

pobox_list: Gave a P.O. Box as an address		
Label	Frequency	Percent
Did not give a P.O. Box	7,594	87.7
Did give a P.O. Box	1,067	12.3

race_amerindian: Identify as American Indian/Alaska Native		
Label	Frequency	Percent
No	8,187	94.5
Yes	474	5.5

race_asian: Identify as Asian		
Label	Frequency	Percent
No	8,339	96.3
Yes	322	3.7

race_black: Identify as Black		
Label	Frequency	Percent
No	8,393	96.9
Yes	268	3.1

race_hisp: Identify as Spanish, Hispanic, or Latino		
Label	Frequency	Percent
No	7,801	90.1
Yes	860	9.9

race_other: Identify as other race		
Label	Frequency	Percent
No	8,020	92.6
Yes	641	7.4

race_pacific: Identify as Native Hawaiian or Pacific Islander		
Label	Frequency	Percent
No	8,574	99.0
Yes	87	1.0

race_white: Identify as White		
Label	Frequency	Percent
No	1,393	16.1
Yes	7,268	83.9

self_list: Individual signed him/herself up on the lottery list		
Label	Frequency	Percent
Did not sign self up	1,481	17.1
Signed self up	7,180	82.9

zip_msa_list: Zip code from lottery list is a MSA		
Label	Frequency	Percent
Zip code of residence not in MSA	2,253	26.0
Zip code of residence in MSA	6,408	74.0

Appendix 2 – Condensed Equation Dummy Variable Key

Dummy Variable Categories	
Expanded Equation	Condensed Equation
Demographic Variables	
race_white	White
race_amerindian	Not White
race_asian	
race_black	
race_hisp	
race_other	
race_pacific	
Education & Employment Variables	
employ_det	
Employed	Employed
Self-employed	
Not Employed	Unemployed
Retired	
employ_hrs	
Does not work	No Work
Work <20 hrs/week	Part Time Work
Work 20-29 hrs/week	
Work 30+ hrs/week	Full Time Work

Household Income and Size Variables	
hhinc_cat	
$0	
$1 - $2,500	
$2,501 - $5,000	
$5,001 - $7,500	Below $15,000
$7,501 - $10,000	
$10,001 - $12,500	
$12,501 - $15,000	
$15,001 - $17,500	
$17,501 - $20,000	
$20,001 - $22,500	
$22,501 - $25,000	Between $15,001 and $30,000
$25,001 - $27,500	
$27,501 - $30,000	
$30,001 - $32,500	
$32,501 - $35,000	
$35,001 - $37,500	
$37,501 - $40,000	
$40,001 - $42,500	Over $30,001
$42,501 - $45,000	
$45,001 - $47,500	
$47,501 - $50,000	
>$50,000	
numhh_list	
Signed self up	Signed Self Up
Signed self up + 1 additional person	Signed Up Additional People
Signed self up + 2 additional people	

Glossary

Cost Sharing - The share of costs covered by one's insurance that are paid out of his/her own pocket. This term generally includes deductibles, coinsurance, and copayments, or similar charges, but it doesn't include premiums, balance billing amounts for non-network providers, or the cost of non-covered services (Healthcare.gov).

Federal Poverty Line - A measure of income issued every year by the Department of Health and Human Services (HHS). Federal poverty levels are used to determine one's eligibility for certain programs and benefits, including savings on Marketplace health insurance, and Medicaid and CHIP coverage (Healthcare.gov).

Marketplace – Shorthand for the "Health Insurance Marketplace," a shopping and enrollment service for medical insurance created by the Affordable Care Act in 2010 (Healthcare.gov).

Medicaid - Insurance program that provides free or low-cost health coverage to some low-income people, families and children, pregnant women, the elderly, and people with disabilities (Healthcare.gov).

Medicare - A federal health insurance program for people 65 and older and certain younger people with disabilities (Healthcare.gov).

Metropolitan Statistical Area (MSA) - An MSA consists of one or more counties that contain a city of 50,000 or more inhabitants or contain a Census Bureau-defined urbanized area (UA) and have a total population of at least 100,000 (Census Bureau).

Open Enrollment Period – The yearly period when people can enroll in a health insurance plan. Outside of the Open Enrollment Period, one generally can enroll in a health insurance plan only if he/she qualifies for a Special Enrollment Period. One is eligible if he/she has certain life events, like getting married, having a baby, or losing other health coverage (Healthcare.gov).

Oregon Health Insurance Experiment (OHIE) – The Oregon Health Insurance Experiment is a landmark study of the effect of expanding public health insurance on healthcare use, health outcomes, financial strain, and well-being of low-income adults (www.nber.org/Oregon/).

Patient Protection and Affordable Care Act (Affordable Care Act or ACA) - The first part of the comprehensive healthcare reform law enacted on March 23, 2010. The law provides numerous rights and protections that make health coverage more fair and easy to understand, along with subsidies (through "premium tax credits" and "cost-sharing reductions") to make it more affordable. The law also expands the Medicaid program to cover more people with low incomes (Healthcare.gov).

Policy Take-Up - The participation of eligible people in government health insurance programs.

Private Insurance - Type of plan usually present in larger companies where the employer itself collects premiums from enrollees and takes on the responsibility of paying employees' and dependents' medical claims. These employers can contract for insurance services such as enrollment, claims processing, and provider networks with a third-party administrator, or they can be self-administered (Healthcare.gov under "Self-Insured Plan").

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