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# Three Essays on Healthcare Economics

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# THREE ESSAYS ON HEALTHCARE ECONOMICS

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by

Esteban Chinchilla

2022

To: Dean John F. Stack, Jr.
Steven J. Green School of International and Public Affairs

This dissertation, written by Esteban Chinchilla, and entitled Three Essays on Healthcare Economics, having been approved in respect to style and intellectual content, is referred to you for judgment.

We have read this dissertation and recommend that it be approved.

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## DEDICATION

To my wife Karla, your love, unconditional support, and understanding all these years gave me the strength and motivation to accomplish this goal. To my daughter Valentina, you were born during the qualifying examinations week and have brought me unlimited happiness ever since. I hope this accomplishment inspires you to value and love education as much as I do. To the loving memory of my father, you will always be my hero and I will continue to miss you every day, and to my grandmother Lucia, whose kindness and smile continues to live on. To my mother, your support and sacrifices helped me be where I am today.

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ABSTRACT OF THE DISSERTATION

THREE ESSAYS ON HEALTHCARE ECONOMICS

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This dissertation follows a three-essay format. The first chapter examines the impact of a home visiting program on medical expenses and healthcare services utilization implemented by a healthcare maintenance organization. The evaluation uses administrative claims data to estimate the six-month average expenditures following program enrollment. The estimation is carried out by applying a difference-in-differences method to compare spend for patients enrolled in the program to a control group. Estimation using matching methods to address any potential confounding bias is also applied to support estimates and confirms findings. The estimation finds that the program increases average medical expenditures by as much as 30% in the six-month period following enrollment, suggesting it is an ineffective cost control strategy.

The second chapter explores the use of individuals' preferences regarding their willingness to accept payments to quit smoking to identify and target interventions for smoking cessation during pregnancy. Unlike prior studies, which focus on individuals' willingness to pay for and use smoking cessation products, quit rates are estimated using individuals' willingness to accept a stream of payments in exchange for smoking cessation. Estimation via regression analysis techniques finds that when individuals are willing to accept payments, delivery of a subsequent monetary incentive can increase quit rates by an average of 20%. These results suggest that willingness to

accept monetary incentives to quit smoking is an effective mechanism to identify participants with a higher chance of successful smoking cessation attempts.

The third chapter builds on the prior chapter by analyzing the reliability of using self-reported quit rates to measure campaign effectiveness, comparing them to urine cotinine levels measured using laboratory-based tests. Public health campaigns often do not have access to laboratory test results to measure the participants' urine cotinine levels because of the associated costs and the complexity of obtaining testing samples. The use of self-reported indicators offers a low-cost mechanism to measure campaign success with significantly easier implementation of results monitoring. Findings show that self-reports overstate quit rates by an average of 11%, providing a frame of reference that allows campaign officials to interpret self-reported data to evaluate campaign effectiveness and performance.

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| | |
|---|---|
| ATT | Average effect of the treatment on the treated |
| CAD | Coronary artery disease |
| CCI | Charlson Comorbidity Index |
| CHF | Congestive heart failure |
| COPD | Chronic obstructive pulmonary disease |
| DID | Difference-in-differences |
| ESRD | End-stage renal disease |
| OLS | Ordinary least squares |
| PSM | Propensity score matching |
| WTA | Willingness-to-accept |
| WTP | Willingness-to-pay |
| WTU | Willingness-to-use |

CHAPTER 1

# INTRODUCTION

## 1.1 Introduction

This dissertation is composed of three empirical essays on healthcare economics. In the first chapter, I evaluate the cost-effectiveness of a Medicare Advantage organization's home-visiting program. In the second chapter, co-authored with Alejandro Arrieta, Ph.D., we seek to analyze pregnant smokers' preferences regarding their willingness to accept monetary incentives for smoking cessation as a mechanism to identify and target interventions. Lastly, in the third chapter, co-authored with Alejandro Arrieta, Ph.D., we seek to analyze the efficiency of self-reported smoking quit rates by pregnant women as a measure of smoking cessation campaign effectiveness.

In the first chapter, I analyze a home-visiting initiative implemented by a regional Medicare Advantage organization. Hospital expenses are historically one of the main cost drivers in healthcare expenditures in the U.S., leading healthcare maintenance organizations (HMOs) to create cost containment initiatives in an attempt to prevent hospitalizations. The program consisted of identifying participants and contacting them for subsequent enrollment in a program that consisted of sending a healthcare provider to a patient's home for an initial visit, with follow-up visits as needed to provide care and guidance post-discharge for a period of between two and six months. The organization's goal to reduce expenses is measured by dollars spent on medical expenses in the six-month period following program enrollment. A control group is constructed by identifying individuals who were deemed eligible to participate in the program but were not enrolled due to program capacity constraints. A difference-in-differences estimation method is then used to compare total medical expenses in

the 6-month period following enrollment to the expenses incurred by the health plan for those who were enrolled in the program. I subsequently apply a propensity score matching method in an attempt to address the bias due to confounding variables and invert the treatment and control groups as additional robustness checks. Results estimated using matching methods further confirm findings. I conclude that the home-visiting program results in an estimated 30% increase in medical expenses in the 6-month period following enrollment, suggesting that these programs may not be effective as cost-containment initiatives.

In the second chapter, we analyze results from a clinic-based smoking cessation program for pregnant women that offered monetary incentives to quit smoking. In addition to offering different levels of monetary incentives, the program collected urine samples and measured cotinine levels during each prenatal office visit, as well as having participants complete a questionnaire. The research literature has often explored individuals' pricing for quitting by leveraging their willingness to pay for smoking cessation products as well as their willingness to use these methods. However, willingness to accept monetary incentives to stop smoking has not been explored. The use of monetary incentives has been explored in the literature and shown to be effective in reducing smoking prevalence. Our objective is to analyze the data obtained during the clinic-based program to understand the efficiency of using individuals' preferences regarding their willingness to accept payments as an incentive for smoking cessation as a leading indicator to target interventions. Furthermore, we explore the role a monetary incentive plays in those individuals who exhibit an affirmative willingness to accept payments for smoking cessation. Our findings show that participants willing to accept a monthly cash incentive to stop smoking will exhibit increased quit rates only when a monetary incentive is given to them, and there will be no change when the incentive is not given. These results suggest that the commitment device

requires a monetary and a non-monetary component to achieve a reduction in smoking prevalence. These findings have policy implications and could influence campaign implementation design, as leveraging questionnaires asking participants about their willingness to accept a monetary incentive to stop smoking as the eligibility criteria to target the intervention can lead to increased quit rates once the subsequent delivery of the monetary incentive takes place.

In the third chapter, we build on the findings obtained from the smoking cessation study to analyze the use and efficiency of self-reported quit rates by participants. Public health campaigns may not be able to collect urine samples to measure the effectiveness of smoking cessation initiatives using laboratory-based cotinine levels. In addition to the practical challenges and obstacles in collecting individual urine samples, there is an associated cost with each laboratory-based urine cotinine test. An alternative measurement of smoking cessation could be implemented by asking participants about their use of nicotine, but using participants' self-reported outcomes introduces significant disadvantages and biases that distort results and reduce the reliability and credibility of estimations. However, being able to observe both the participants' responses regarding their tobacco use and their true urine-cotinine levels measured in a laboratory allow for a better understanding of the accuracy and reliability of self-reported quit rates in the context of real measurable results. This allows for public health campaign designs that leverage the low cost of implementation of smoking cessation data collection methods We construct a measure of quit rate using self-reported data collected on the questionnaire administered during each prenatal visit and compare it to the real quit rate as measured using the urine cotinine level from a laboratory test. We find that quit rates reported by participants are, on average, overstated by 11%, providing a framework of reference that can be used

to better understand the effectiveness of large-scale smoking cessation public health campaigns.

CHAPTER 2

# HEALTHCARE AT HOME: IMPACT OF HOME-VISITING PROGRAMS ON MEDICAL EXPENSES AND HEALTHCARE SERVICES UTILIZATION

## 2.1 Introduction

Healthcare maintenance organizations and provider groups often design and implement programs and cost-saving initiatives targeting patients at high risk of either admission or readmission into a hospital to avoid the high costs associated with hospitalizations. These programs typically consist of either primary care doctors or nurse practitioners visiting patients at their place of residence for a predetermined period of time, with the intention of better managing a patient's health and avoiding subsequent hospital admissions and the costs associated with them. These programs are typically composed of primary care activities such as wound care, medication reconciliation, post-discharge guidance, and assessment of future risks.

When targeting hospital readmissions, identifying patients for program enrollment with accuracy is essential because these activities have limited impact on patients according to the severity of the initial episode that led to the admission. In the first group, there are patients with an extremely high probability of being readmitted that these programs cannot reach or positively affect the outcome. The readmission is almost inevitable. There is a second group composed of members who can be positively affected by these programs, and the activities surrounding these programs can successfully avoid readmissions. Lastly, there is the group not readmitted because the initial hospitalization was due to a low acuity episode.

Home-visiting programs implemented by HMOs generally have a goal of reducing medical expenses incurred by their memberships. Typically implemented through partnership with a provider group, the cost per visit paid to the healthcare provider attempts to offset future medical costs. This paper applies econometric methods to measure the effectiveness of a private program as a medical expenses savings initiative.

The remainder of this chapter is organized as follows: Section Literature review is a review of the relevant literature. In section Program design, we describe the program design implementation details. In section Methods, we describe the empirical methods used. In section Results, we discuss the results of our estimation. Lastly, in section Conclusion we provide concluding remarks.

## 2.2 Literature review

Healthcare maintenance organizations often design and implement case management programs that focus on delivering personalized managed care. Case management is the collaborative process of assessment, planning, facilitation, care coordination, evaluation, and advocacy for options and services to meet an individual's and family's comprehensive health needs through communication and available resources to promote quality cost-effective outcomes (ACMA (2020)). When implemented at health insurance companies, these activities have a goal to not only improve the health status of the patient but also to obtain cost-effective outcomes and efficiencies, reducing the overutilization of healthcare services.

The activities that case management is composed of can be categorized into education, compliance, care coordination, utilization management, and transition management. Education activities ensure that both the healthcare team as well as the patients are

aware of all available resources and benefits that are relevant to the progression of care. Compliance tasks ensure that all disciplines operate within all applicable regulations and policies. Transition management ensures the arrangement of all elements that need to be in place to successfully implement a transition plan that supports the healthcare team and the patient along with the primary caregiver. The remaining two categories are especially relevant to this paper. Care coordination begins with screening and identifying patients where diverse factors could interfere with the progression of care. To this end, specific criteria are defined to stratify patients in need of case management services and deliver a plan of care. The utilization management component of case management refers to the method and activities carried out to deliver the appropriate level of care by following evidence-based guidelines, where early interventions can keep the patients' health from deteriorating, which could mean additional expenses brought about by complications.

Given the significance of social determinants of health in the context of the complexities of medical care, case management activities often include home-visiting programs. These home-visiting programs -often referred to as "Healthcare At-Home" programs- are a collaborative effort to avoid hospitalizations where medical doctors, nurses, and care coordinators work together by planning, coordinating, and monitoring healthcare services for one to six months. During this time, primary care providers visit patients at their place of residence, providing care to them, aiding with wound care, medication reconciliation, and in cases where the intervention takes place after the patient was discharged from a hospital, help with interpreting discharge instructions, among other care-related activities. Having medical resources on staff assigned to a case management team and healthcare professionals visiting patients to actively manage patients' health can be a costly activity that can reduce savings from avoidance of medical expenses.

When looking at official estimates of total healthcare spending in the United States published by the Centers for Medicare & Medicaid Services (CMS), hospital care has historically represented the largest share with an average of 33% of total expenditures (Hasche, Ward, and Schluterman (2017)). The cost of hospital care has been consistently the highest expense when managing a Medicare patient's health, driving health plans to launch initiatives to attempt to control and reduce inpatient admissions and associated expenditures. To this end, HMOs often focus on reducing hospitalizations by targeting patients who are not only at high risk of being admitted into a hospital but also present an opportunity where timely intervention can steer them away from hospital admission. Ambulatory care-sensitive conditions (ACSCs) can be used as a reference to identify such opportunities because preventing the onset of or managing these conditions by timely outpatient care interventions can reduce the risk of hospitalization (Billings, Zeitel, Lukomnik, Carey, Blank, and L. Newman (1993)). Home-visiting programs are then an attractive intervention because they cannot only present an opportunity to perform a timely intervention but also address differences in access to care associated with patients' socioeconomic status, which can explain the variation in hospitalization rates (Billings, G. M. Anderson, and L. S. Newman (1996)).

Since the creation of Medicare, providing healthcare to the elderly at home has been the subject of debate. One obstacle in implementing such programs is the identification of cases for targeted intervention. A three-year randomized control trial study of case finding and surveillance in patients aged 65 and over found that visits to the general practitioner's office can be lowered by the implementation of a home-visit program (Pathy, Bayer, Harding, and Dibble (1992)). This indicates that there is an opportunity for utilization management in at least one category of service, and while

hospitalization rates were not shown to differ between groups, the average length of stay was shown to be significantly lower.

The elderly population who lives at home on their own and are at risk of functional decline are particularly interesting in home-visiting programs because functional autonomy levels can be better evaluated. Administering an assessment of risk factors for functional decline and the subsequent referral to their general practitioner for diagnosis and intervention has been shown to be effective in reducing loss of autonomy (Robichaud, Hébert, P. Roy, and C. Roy (2000)). A randomized control study of case finding and surveillance of patients aged 65 and older showed that mortality was significantly lower in the intervention group, and while hospital admissions did not differ between groups, the length of stay was much shorter in the intervention group as well (Pathy et al. (1992)). This would indicate that there is an opportunity to reduce the utilization of healthcare services associated with loss of autonomy or function. I do not explore the impact on savings specifically attributable to functional decline but rather on medical expenses as a whole.

There is at least some evidence showing that interventions using functional deterioration as eligibility criteria are effective with those patients that are at low risk of functional impairment, with those at high risk not experiencing favorable intervention effects and an unfavorable increase in nursing home admissions (Stuck, Minder, Peter Wuest, Gillmann, Egli, and Kesselring (2000)). Studies focusing on falls and impairments in mobility as outcomes found no clear evidence that home-visiting programs are an effective preventive intervention (van Haastregt, Diederiks, van Rossum, de Witte, Voorhoeve, and Crebolder (2000)). The uncertainty about whether home-visiting programs can reach only specific subgroups suggests that the identification criteria for patients eligible to participate in the program could influence the out-

come (Dalby, Sellors, F. Fraser, C. Fraser, van Ineveld, and Howard (2000). This issue remains largely unaddressed, as there seems to be no consensus in the literature regarding identification methods.

The program evaluated in this paper implemented easily reproducible eligibility criteria that relied on the identification of six chronic conditions and a comorbidity measure widely documented, explicitly introducing into the literature the identification criteria used to determine program eligibility. I measure the effectiveness of the home-visiting program as a cost savings initiative by implementing a difference-in-differences estimation, and subsequently apply propensity score matching in an attempt to confirm findings by reducing the bias due to confounding variables.

## 2.3 Program design

The program relies on an automated daily process that analyzes the clinical history of all patients by examining administrative data. Those that meet the enrollment eligibility criterion are flagged as eligible for participation in the program. The criteria to be considered eligible are based upon a summary comorbidity measure along with the presence of two or more out of a list of six specific conditions, or the simultaneous presence of three specific conditions.

The summary comorbidity measure used is the Charlson Comorbidity Index (CCI), which was originally developed to predict mortality within one year following a hospital admission in patients with no trauma. To be deemed as eligible, a patient needs to have a CCI score of 5 or more, along with the presence of two or more out of the following markers: chronic obstructive pulmonary disease (COPD), congestive heart failure (CHF), coronary artery disease (CAD), diabetes, cancer, or the presence of

behavioral health disorders (only triggers for the behavioral health marker are depression not further specified, major depressive disorder, bipolar disorder, schizophrenia, alcohol related disorders, and drug related disorders). The simultaneous presence of COPD, CHF and diabetes also flags patients as eligible for enrollment, regardless of their CCI score or presence of other conditions.

A list of eligible patients is calculated daily and the order of patients is randomized. The list is processed in order by case managers, who call the patients providing information about the program and offering enrollment. Patients can then opt-in or reject enrollment. Patients are taken off the list after three unsuccessful attempts to contact them.

There is a maximum number of patients who can be enrolled in the program at a given time which is caused by budget and capacity constraints. The visiting primary care provider group was external to the HMO, representing a cost per visit. Staff capacity also limited enrollment, as there was a limited number of available case managers at the health plan. Case managers assigned a full number of cases do not initiate enrollment calls, even if the list still has eligible patients. As patients leave the program, new patients can then be enrolled.

Once enrolled, patients remain in the program for a minimum of two months and up to six months. During this time, a primary care physician or a nurse practitioner is sent to the patient's home for an initial visit with follow-up visits as needed. At each visit, the healthcare provider determines the date of the next visit as well as if continued enrollment is necessary if the patient is within the two- to six- month enrollment period.

## 2.4 Data

The data used in this study is composed of anonymized (de-identified and non-coded data) medical and pharmacy paid claims for a total of 1,194 Medicare beneficiaries, spanning from years 2009 to 2015. There are 1,272 females and 1,052 males in the sample, out of which 266 have qualified for Medicare eligibility due to disability. The control group consists of 996 patients, while the treatment group has 1,328 patients. The data set has been refreshed three years after the end of the measurement period, allowing for an ample claims run-out period and minimizing changes in paid claims due to lagged factors such as reinsurance recoveries and appeals.

Mortality rates for the two groups is estimated to be 20% of patients in the treatment group, and 9% in the control group. This could suggest that there are systematic errors in the composition of the control group.

Reinsurance provisions that cover medical expenses for members with an unusually high medical cost are in place, but I analyze claims expenses prior to the application of reinsurance recoveries to isolate from differences in contractual terms. Neither healthcare providers nor case managers know if the patient has met the stop-loss threshold. The data set does not contain any transplant cases.

The composition of the control and treatment groups are largely similar, with slightly higher prevalence of ESRD, COPD and CHF in the treatment group. A summary of the data can be found in Table 2.1.

## 2.5 Methods

This study analyzes the effectiveness of the program as measured in terms of dollars spent on medical expenses incurred in the six-month period following enrollment. To do so, I perform a difference-in-differences estimation leveraging the output of the clinical review process to identify patients that have been flagged as eligible but were never enrolled due to capacity constraints and using them as a control group. These patients represent cases that were eligible to receive the intervention but have not been able to do so due to the limited number of personnel to manage their cases.

For each patient, the total medical expenses in the six-month period prior to enrollment in the program, and the six-month period immediately following enrollment have been calculated. To account for the variation in utilization of healthcare services brought by seasonality and the utilization patterns that follow the calendar year, medical expenses have been aggregated by month and normalized using a seasonality adjustment factor. This would account, for example, for increased utilization during flu season, or periods of low utilization that coincide with the Medicare enrollment process. The seasonality adjustment factor has been calculated by adding up medical expenses for approximately 31,000 Medicare beneficiaries by each age and gender group combination for a calendar year, with that value taken as a factor of 1. Then the aggregate medical expenses for each age group have been calculated for each calendar month, and a seasonality factor has been determined relative to the yearly mean for that age and gender group. Table 2.2 shows the seasonality factors used for each age and gender group. The monthly medical expenses total for each patient has been adjusted using this factor and then added up for the six-month period prior to enrollment and immediately after enrollment. This allows for the comparison of members enrolled at different times of the year using normalized expenses.

Eligibility for program enrollment is triggered by a summary score measuring comorbidities combined with the presence of specific conditions. In this respect, eligibility to the program has not been determined by medical expenses incurred by the patient, but rather by care needs.

The treatment and control groups can be considered stable for repeated cross-sections of the data, with a similar distribution of age and gender across years.

The proposed model is a log-linear difference-in-differences estimation of the form:

$$\begin{aligned} ln(Expenses_{it}) = \beta_0 &+ \beta_1\ Period_{it} + \beta_2\ StudyGroup_{it} \\ &+ \beta_3(Period_{it}\ \times\ StudyGroup_{it}) + \beta_4\ COPD_{it} \\ &+ \beta_5\ CHF_{it} + \beta_6\ Diabetes_{it} + \beta_7\ Asthma_{it} \\ &+ \beta_8\ BehavioralHealth_{it} + \beta_9\ Cancer_{it} \\ &+ \beta_{10}\ ESRD_{it} + \gamma\ Demo_{it} \\ &+ \delta\ DiseaseInteractions_{it} + \epsilon_{it} \end{aligned} \tag{2.1}$$

The model includes controls for seven major condition categories, a vector *Demo* made up of demographic variables that includes gender, age and race, and a vector ($Interactions$) of binary variables with the interaction terms between, CHF, diabetes, asthma, COPD, behavioral health, cancer and ESRD, capturing the simultaneous presence of two chronic conditions.

The conditions have been identified by processing administrative claims data and mapping ICD-10 diagnosis codes to each condition, as outlined in Table 2.3.

Medical expenses are normalized to account for patients' differences in conditions and comorbidities and the different level of spending necessary for appropriate treatment. This allows us to isolate the effect of the program and compare individuals with different conditions. To achieve this, medical expenses have been risk-stratified and normalized using the Charlson Comorbidity Index as it is considered an adequate adjustment mechanism (Austin, Wong, Uzzo, Beck, and Egleston (2015)). Additionally, claims paid amounts do not reflect reinsurance recoveries to avoid distorting expenses.

Next, I apply propensity score matching to adjust for baseline confounding and balance the treatment group, and calculate the average effect of the treatment on the treated (ATT). I estimate the probability of being treated given a set of pre-treatment covariates using the propensity score. After careful examination of the region of common support, I select and execute the nearest neighbor propensity score matching algorithm.

Once the matching sample is obtained, I proceed to assess covariate balance. As a first step I plot the propensity score estimate against the mean of each covariate. Both the treatment and control groups display similar means of each covariate at each value of the propensity score, with minimal departure at higher values of the propensity score.

The second step in my covariate balance assessment is to formally test the difference-in-means for each covariate in the model, observing that I cannot reject the null hypothesis that there is no mean difference for each covariate. The last step is to create

a measure of the average imbalance by computing the average absolute standardized difference ("standardized imbalance"), which takes the form:

$$\left|\frac{\bar{\beta}}{\sigma}\right| = \frac{1}{k}\sum_{x}\frac{|\beta_x|}{\sigma_x} \tag{2.2}$$

where $\beta_x$ captures the difference between the mean of our control and treatment group in the matched sample for covariate $x$. I can observe that there are small differences between both groups because the average absolute standardized difference is close to 0 (0.017 for the standard group estimation, and -0.004 for the inverted groups).

After estimating the treatment effects, I invert the control and treatment groups and apply the same propensity score matching procedures to estimate the average treatment effect of the treated on the untreated group to address any systematic difference between the treated and the untreated subjects.

## 2.6 Results

As a first step, I run a difference-in-differences model without any control variables. Table 2.4 - Model 1 shows the results of regressing medical expenses adjusted for seasonality, but without adjusting for risk or controlling for comorbidities. The parameter estimate suggests that the treatment group incurred expenses that are on average 35% higher than the control group ($DID$ coefficient is our difference in differences estimator). Running the same basic model but adjusting the medical expenses for risk and comorbidities (Table 2.4 - Model 2), shows that expenses for the treatment group are 28% higher on average, which is consistent with the first model.

Estimating the model after the inclusion of demographics controls as well as controlling for the presence of chronic conditions shows that the treatment group actually incurred medical expenses 31% higher than the treatment group (Table 2.4 - Model 3). This result is statistically significant and it represents substantial evidence against the null hypothesis, which we can reject at the 1% level. I then proceed to estimate the model by adding the disease interaction terms, obtaining similar results (Table 2.4 - Model 4) - only 0.02% lower than the first estimation.

I then repeat the procedure by running the models with control variables with and without the disease interaction terms (Models 3 and 4), but this time using medical expenses adjusted for comorbidities (Table 2.4 - Models 5 and 6 respectively). The results are consistent with my previous findings both in terms of statistically significance and the magnitude of the parameter estimate.

Lastly, the results shown on Table 2.4 - Models 7 and 8 correspond to the pair of regressions used in the previous steps, but this time excluding pharmacy claims, because this would represent Medicare Part A and Part B claims alone (specialty drugs that are typically classified as Part B instead of Part D have been excluded as well). This allows for the identification of cost trends that are isolated from cost variances emanating from the price difference between brand-name and generic drugs, and high-cost specialty drugs. Once again, the point estimates are consistent in magnitude and statistical significance as previously seen, suggesting that hospital expenses dominate cost.

The parameter estimates for diabetes, behavioral health disorders, and cancer remain consistent cost drivers across all models. Behavioral health and congestive heart

failure seem to be conditions that also increase expenses when found in the presence of other conditions, as the statistical significance of the interaction terms suggest.

The difference-in-difference estimates show strong evidence that the program actually increases medical expenditures -on average- by approximately 31% in the short run. These findings are supported by the propensity score matching estimates produced as a robustness check. Table 2.5 shows the results for treatment and control groups (standard model), as well as the inverted groups. The average treatment effect of the treated estimated by a reduced form OLS model using the matched sample is a 35.49% (SE 0.07) increase in medical expenses. Figure 2.1 shows the estimated propensity scores by treatment status, along with the region of common support. All graphs for the covariate balance plots can be found in Figure 2.2.

Once the groups are inverted, the average treatment effect of the treated estimated for the untreated group is -26.94% (SE 0.08). Estimates have similar magnitudes and signs with those obtained with the original groups and the DID estimation, suggesting results consistency across estimation methods. Figure 2.3 shows the estimated propensity scores by treatment status, along with the region of common support for the inverted groups. All corresponding graphs for the covariate balance plots can be found in Figure 2.4.

Table 2.6 shows that the difference in means between the control and treatment groups is statistically significant for the parameters of interest, a result that is also consistent when the control and treatment groups are swapped as a robustness check to our matching method (Table 2.7).

## 2.7 Conclusion

The difference-in-differences model shows that the treatment group incurred expenses are on average 35% higher than the control group. When estimating expenses, including demographics controls as well as controlling for the presence of chronic conditions in the model shows that the treatment group actually incurred medical expenses that are 31% higher than the control group. Estimates obtained using models that include disease interaction terms had similar results. Results are consistent across model specifications in terms of statistical significance and the magnitude of the parameter estimates.

The exclusion of pharmacy claims to isolate medical cost trends from cost variances that originate in the high variability of drug costs due to the price difference between brand-name and generic drugs as well as the high cost of specialty drugs, shows point estimates consistent in magnitude and statistical significance.

Diabetes, behavioral health disorders, and cancer remain consistent cost drivers across all models. It is not surprising that diabetes is a cost driver because this program would most likely assist patients not previously well-controlled for their condition with medication adherence (Gonzalez, Safren, Cagliero, Wexler, Delahanty, and E (2007)). Diabetes prevalence for Medicare beneficiaries is 18.9%, with annual costs among beneficiaries $ 500 higher than those without diabetes (Hasche et al. (2017)). Behavioral health disorders also interfere with medication and treatment adherence, an issue that once mitigated through intervention can drive medical expenses upwards. Both behavioral health and cancer are consistent across regressions because they can be considered the main determinants of healthcare cost (Meerding, Bonneux, Polder, Koopmanschap, and van der Maas PJ 1998).

The disease interaction between diabetes and behavioral health is statistically significant, with a possible interpretation being the link between some psychological disorders (depression and schizophrenia, both captured in the $BehavioralHealth$ control variable) and diabetes (Balhara (2011)). This association results in higher medical resource utilization for both inpatient and outpatient settings and higher pharmacy costs (Hutter, Schnurr, and Baumeister (2010)).

While there are health benefits associated with visiting programs (Pathy et al. (1992), Leveille, Wagner, Davis, Grothaus, Wallace, LoGerfo, and et al. (1998), Robichaud et al. (2000)), there is at least some evidence discrediting these findings (Stuck et al. (2000), Dalby et al. (2000), van Haastregt et al. (2000)). The results from this study provide additional evidence that can complement the results of health outcomes, providing an additional decision point for policy and program implementation, while introducing clear parameters for the implementation of a home-visiting program eligibility criteria.

Competing initiatives implemented by the plan have not been identified - There were no new formal medical expense savings initiatives implemented during the period being studied in this paper, outside the ones already being carried out as part of normal operations.

Difference-in-difference estimates show strong evidence that in the short run the program actually increases medical expenditures on average by approximately 31% and that any intended cost savings from hospitalization cost reduction are not enough to offset the increased cost by more intensely and actively managing patients' care. These preliminary results suggest that home-visiting programs are an ineffective cost-savings strategy.

The subsequent application of a propensity score matching method of estimation shows consistent results for treatment and control groups, as well as the inverted groups. The average treatment effect of the treated shows a 35.49% increase in medical expenses, while the average treatment effect of the treated estimated for the untreated group is -26.94%. The magnitude and sign similarity of the parameter estimates suggest results are consistent across the PSM and DID estimation methods.

This study focuses on the short-term outcome of medical expenses, measuring only the six-month period following treatment. Costs associated with implementing the program have been excluded from the study to avoid introducing variation due to differences in contracted rates for the visiting physicians, but can be incorporated into the analysis for a more accurate impact assessment. However, unless there is variance in the intervention itself at the time of visit driven by contractual parameters, leaving these costs out provided evidence that the program is not effective in the short run as a medical expenses savings initiative.

Further research is recommended; looking at larger post-treatment time periods may yield different results than those of this study. Additionally, incorporating into the study the effect of home visits on Medicare risk scores -and therefore, on revenue through increased premium payments to the plan- may provide another view on the cost-effectiveness of home-visiting programs. Exploring the effect of the visiting program on health outcomes, mortality, or survivability can be directions in which further research could add to the findings.

Table 2.1: Data

| Group | Variable | N | Frequency | Percent | Mean | SD |
|---|---|---|---|---|---|---|
| Control | Age | 996 | | | 77.16 | 10.35 |
| | Gender | 996 | 464 | 46.6% | 0.44 | 0.50 |
| | COPD | 996 | 208 | 20.9% | 0.21 | 0.41 |
| | CHF | 996 | 146 | 14.7% | 0.15 | 0.35 |
| | Diabetes | 996 | 634 | 63.7% | 0.64 | 0.48 |
| | Asthma | 996 | 88 | 8.8% | 0.09 | 0.28 |
| | Behavioral health | 996 | 330 | 33.1% | 0.33 | 0.47 |
| | Cancer | 996 | 306 | 30.7% | 0.31 | 0.46 |
| | ESRD | 996 | 6 | 0.6% | 0.01 | 0.08 |
| Treatment | Age | 1,328 | | | 74.46 | 11.43 |
| | Gender | 1,328 | 588 | 44.3% | 0.44 | 0.50 |
| | COPD | 1,328 | 432 | 32.5% | 0.33 | 0.47 |
| | CHF | 1,328 | 370 | 27.9% | 0.28 | 0.45 |
| | Diabetes | 1,328 | 898 | 67.6% | 0.68 | 0.47 |
| | Asthma | 1,328 | 156 | 11.7% | 0.12 | 0.32 |
| | Behavioral health | 1,328 | 536 | 40.4% | 0.40 | 0.49 |
| | Cancer | 1,328 | 482 | 36.3% | 0.36 | 0.48 |
| | ESRD | 1,328 | 50 | 3.8% | 0.04 | 0.19 |
| Total | Age | 2,324 | | | 75.66 | 11.04 |
| | Gender | 2,324 | 1,052 | 45.3% | 0.44 | 0.50 |
| | COPD | 2,324 | 640 | 27.5% | 0.28 | 0.45 |
| | CHF | 2,324 | 516 | 22.2% | 0.22 | 0.42 |
| | Diabetes | 2,324 | 1,532 | 65.9% | 0.66 | 0.47 |
| | Asthma | 2,324 | 244 | 10.5% | 0.10 | 0.31 |
| | Behavioral health | 2,324 | 866 | 37.3% | 0.37 | 0.48 |
| | Cancer | 2,324 | 788 | 33.9% | 0.34 | 0.47 |
| | ESRD | 2,324 | 56 | 2.4% | 0.02 | 0.15 |

Table 2.2: Seasonality adjustment factors

| Gender | Age Group | January | February | March | April | May | June | July | August | September | October | November | December |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Female** | **65-69** | 1.477 | 1.510 | 1.531 | 1.506 | 1.472 | 1.493 | 1.504 | 1.520 | 1.458 | 1.462 | 1.418 | 1.362 |
| | **70-74** | 1.746 | 1.752 | 1.873 | 1.735 | 1.705 | 1.609 | 1.656 | 1.655 | 1.601 | 1.641 | 1.621 | 1.667 |
| | **75-79** | 1.370 | 1.453 | 1.327 | 1.385 | 1.442 | 1.535 | 1.391 | 1.451 | 1.407 | 1.414 | 1.512 | 1.548 |
| | **80-84** | 1.154 | 1.096 | 1.087 | 1.158 | 1.126 | 1.154 | 1.231 | 1.168 | 1.161 | 1.188 | 1.164 | 1.161 |
| | **85-89** | 0.777 | 0.749 | 0.721 | 0.731 | 0.788 | 0.766 | 0.752 | 0.779 | 0.810 | 0.774 | 0.800 | 0.794 |
| | **90-94** | 0.375 | 0.359 | 0.371 | 0.379 | 0.366 | 0.353 | 0.364 | 0.333 | 0.417 | 0.411 | 0.360 | 0.359 |
| | **95+** | 0.102 | 0.081 | 0.090 | 0.105 | 0.102 | 0.091 | 0.101 | 0.093 | 0.145 | 0.110 | 0.125 | 0.108 |
| | **Under 65** | 1.466 | 1.419 | 1.639 | 1.509 | 1.511 | 1.503 | 1.538 | 1.444 | 1.419 | 1.442 | 1.481 | 1.557 |
| **Male** | **65-69** | 1.556 | 1.632 | 1.513 | 1.520 | 1.490 | 1.599 | 1.583 | 1.515 | 1.475 | 1.468 | 1.448 | 1.487 |
| | **70-74** | 1.738 | 1.728 | 1.873 | 1.776 | 1.845 | 1.836 | 1.655 | 1.877 | 1.705 | 1.744 | 1.654 | 1.673 |
| | **75-79** | 1.559 | 1.562 | 1.512 | 1.526 | 1.509 | 1.491 | 1.523 | 1.541 | 1.503 | 1.608 | 1.573 | 1.706 |
| | **80-84** | 1.114 | 1.078 | 1.105 | 1.158 | 1.147 | 1.082 | 1.097 | 1.104 | 1.184 | 1.164 | 1.200 | 1.115 |
| | **85-89** | 0.666 | 0.719 | 0.687 | 0.708 | 0.724 | 0.678 | 0.737 | 0.660 | 0.711 | 0.678 | 0.744 | 0.704 |
| | **90-94** | 0.302 | 0.217 | 0.247 | 0.237 | 0.245 | 0.265 | 0.319 | 0.243 | 0.330 | 0.274 | 0.302 | 0.260 |
| | **95+** | 0.065 | 0.063 | 0.063 | 0.076 | 0.040 | 0.049 | 0.086 | 0.060 | 0.092 | 0.064 | 0.079 | 0.055 |
| | **Under 65** | 1.627 | 1.515 | 1.725 | 1.607 | 1.626 | 1.624 | 1.676 | 1.538 | 1.706 | 1.652 | 1.887 | 1.717 |

Seasonality adjustment factors calculated using average medical expenses by gender and age group

Table 2.3: Disease identification - Mapping of administrative data to conditions

| **Label** | **Disease Category** | **ICD-10 Codes** |
|---|---|---|
| Asthma | Diseases of the Respiratory System | J45 - J45.998 |
| Behavioral Health | Mental, Behavioral, and Neurodevelopmental Disorders | F01-F99 |
| Cancer | Neoplasms | C00-D49 |
| CHF<br>(Congestive Heart Failure) | Diseases of the Circulatory System | A36.81;<br>B33.24;<br>I09.81; I11.0; I13.0; I13.2;<br>I26.0-; I27.0; I27.1; I27.2;<br>I27.20; I27.21; I27.22; I27.23;<br>I27.24; I27.29;<br>I27.81; I27.83; I27.89; I27.9;<br>I28.-; I42.-; I43;<br>I50.1-I50.9; I51.4; I51.5 |
| COPD<br>(Chronic Obstructive Pulmonary Disease) | Diseases of the Respiratory System | J41.0; J41.1; J41.8; J42;<br>J43.0; J43.1; J43.2; J43.8;<br>J43.9; J44.0; J44.1; J44.9;<br>J98.2; J98.3;<br>F17.20x; F17.21x; F17.22x;<br>F17.23x;<br>Z72.0 |
| Diabetes | Diabetes Mellitus | E08-E13 |
| ESRD<br>(End-Stage Renal Disease) | Endocrine, nutritional and metabolic diseases | I12.0; I13.11; I13.2;<br>N18-N18.9; N28.9; N04.9 |

Table 2.4: Regression results

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | Expenses | Norm Exp | Expenses | Expenses | Norm Exp | Norm Exp | Exp No Rx | Exp No Rx |
| PERIOD | -0.859*** | -0.695*** | -0.725*** | -0.723*** | -0.836*** | -0.693*** | -0.836*** | -0.835*** |
| | (0.0994) | (0.0945) | (0.0612) | (0.0609) | (0.0693) | (0.0639) | (0.0693) | (0.0689) |
| SG | 0.858*** | 0.505*** | 0.583*** | 0.563*** | 0.668*** | 0.366*** | 0.668*** | 0.647*** |
| | (0.0931) | (0.0875) | (0.0578) | (0.0579) | (0.0650) | (0.0604) | (0.0650) | (0.0650) |
| DID | 0.353*** | 0.285*** | 0.310*** | 0.308*** | 0.330*** | 0.283*** | 0.330*** | 0.330*** |
| | (0.1319) | (0.1238) | (0.0805) | (0.0801) | (0.0907) | (0.0837) | (0.0907) | (0.0902) |
| AGE | | | -0.0199*** | -0.0193*** | -0.0143*** | -0.0225*** | -0.0143*** | -0.0134*** |
| | | | (0.00188) | (0.00191) | (0.00212) | (0.00200) | (0.00212) | (0.00216) |
| GENDER | | | 0.174*** | 0.185*** | 0.185*** | 0.00672 | 0.185*** | 0.193*** |
| | | | (0.0408) | (0.0413) | (0.0459) | (0.0430) | (0.0459) | (0.0464) |
| RACE | | | 0.0109 | 0.0133 | 0.0102 | 0.00183 | 0.0102 | 0.0136 |
| | | | (0.0102) | (0.0103) | (0.0114) | (0.0108) | (0.0114) | (0.0116) |
| COPD | | | 0.113** | 0.138 | 0.114** | 0.102 | 0.114** | 0.0508 |
| | | | (0.0492) | (0.105) | (0.0551) | (0.108) | (0.0551) | (0.117) |
| CHF | | | 0.203*** | 0.120 | 0.228*** | -0.130 | 0.228*** | -0.0406 |
| | | | (0.0557) | (0.148) | (0.0625) | (0.153) | (0.0625) | (0.166) |
| DIABETES | | | 0.254*** | 0.341*** | 0.152*** | 0.235*** | 0.152*** | 0.179** |
| | | | (0.0430) | (0.0623) | (0.0484) | (0.0660) | (0.0484) | (0.0706) |
| ASTHMA | | | 0.191*** | -0.0404 | 0.180** | 0.225 | 0.180** | 0.0136 |
| | | | (0.0697) | (0.165) | (0.0781) | (0.170) | (0.0781) | (0.184) |
| BH | | | 0.171*** | 0.358*** | 0.142*** | 0.581*** | 0.142*** | 0.319*** |
| | | | (0.0470) | (0.0966) | (0.0527) | (0.100) | (0.0527) | (0.108) |
| CANCER | | | 0.518*** | 0.655*** | 0.601*** | 0.710*** | 0.601*** | 0.683*** |
| | | | (0.0424) | (0.0795) | (0.0476) | (0.0829) | (0.0476) | (0.0893) |
| ESRD | | | 0.920*** | 1.422*** | 0.851*** | 1.568*** | 0.851*** | 1.593*** |
| | | | (0.132) | (0.443) | (0.148) | (0.458) | (0.148) | (0.495) |
| COPD_ESRD | | | | 0.666 | | 2.034*** | | 1.156* |
| | | | | (0.555) | | (0.573) | | (0.620) |
| CHF_ESRD | | | | -0.494 | | -0.618 | | -0.940** |
| | | | | (0.406) | | (0.419) | | (0.454) |
| DIAB_ESRD | | | | -0.237 | | -0.277 | | -0.473 |
| | | | | (0.408) | | (0.422) | | (0.456) |
| ASTH_ESRD | | | | -0.663 | | -1.944* | | -1.261 |
| | | | | (1.126) | | (1.163) | | (1.259) |
| BH_ESRD | | | | 0.112 | | -0.290 | | 0.369 |
| | | | | (0.399) | | (0.412) | | (0.446) |
| CANC_ESRD | | | | -0.765 | | -0.592 | | -0.941* |
| | | | | (0.484) | | (0.500) | | (0.542) |
| COPD_CANC | | | | -0.0224 | | -0.0597 | | 0.00291 |

Table 2.4 (continued)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | Expenses | Norm Exp | Expenses | Expenses | Norm Exp | Norm Exp | Exp No Rx | Exp No Rx |
| | | | | (0.103) | | (0.106) | | (0.115) |
| CHF_CANC | | | | -0.474*** | | -0.140 | | -0.533*** |
| | | | | (0.120) | | (0.124) | | (0.134) |
| DIAB_CANC | | | | -0.0661 | | -0.166* | | 0.00930 |
| | | | | (0.0925) | | (0.0960) | | (0.104) |
| ASTH_CANC | | | | 0.0715 | | -0.00362 | | 0.0811 |
| | | | | (0.148) | | (0.153) | | (0.165) |
| BH_CANCER | | | | 0.0733 | | -0.198* | | 0.105 |
| | | | | (0.0985) | | (0.102) | | (0.110) |
| COPD_BH | | | | -0.0860 | | -0.286** | | -0.103 |
| | | | | (0.109) | | (0.113) | | (0.122) |
| CHF_BH | | | | 0.207* | | 0.179 | | 0.361*** |
| | | | | (0.119) | | (0.123) | | (0.133) |
| DIAB_BH | | | | -0.360*** | | -0.525*** | | -0.410*** |
| | | | | (0.104) | | (0.107) | | (0.116) |
| ASTH_BH | | | | 0.0980 | | 0.164 | | 0.0760 |
| | | | | (0.156) | | (0.162) | | (0.175) |
| COPD_ASTH | | | | 0.0720 | | 0.0811 | | 0.153 |
| | | | | (0.150) | | (0.155) | | (0.168) |
| CHF_ASTH | | | | 0.528*** | | 0.307* | | 0.573*** |
| | | | | (0.166) | | (0.171) | | (0.185) |
| DIAB_ASTH | | | | -0.110 | | -0.247 | | -0.285 |
| | | | | (0.160) | | (0.165) | | (0.179) |
| COPD_DIAB | | | | 0.111 | | 0.136 | | 0.264** |
| | | | | (0.111) | | (0.115) | | (0.124) |
| CHF_DIAB | | | | 0.160 | | 0.218 | | 0.363** |
| | | | | (0.135) | | (0.140) | | (0.152) |
| COPD_CHF | | | | -0.167 | | -0.232* | | -0.282** |
| | | | | (0.120) | | (0.124) | | (0.134) |
| Constant | 9.051*** | 8.647*** | 10.29*** | 10.16*** | 9.637*** | 9.943*** | 9.637*** | 9.532*** |
| | (0.0699) | (0.0667) | (0.154) | (0.160) | (0.173) | (0.167) | (0.173) | (0.180) |
| Observations | 4,540 | 4,540 | 4,590 | 4,590 | 4,540 | 4,508 | 4,540 | 4,540 |
| R-squared | 0.1316 | 0.078 | 0.209 | 0.220 | 0.187 | 0.162 | 0.187 | 0.200 |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 2.5: Treatment effect estimates of matched samples

| Groups | Estimate | Std. Error | t value | Pr(> \|t\|) | Significance | Adj. R-squared |
|---|---|---|---|---|---|---|
| Standard | 0.35481 | 0.07233 | 4.905 | 1.02E-06 | *** | 0.01234 |
| Inverted | -0.26942 | 0.08223 | -3.27 | 0.00108 | ** | 0.006632 |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 2.6: Difference-in-means; t-tests

| Variable | t | df | p-value | 95% ; C.I. | Mean in Group 1 | Mean in Group 2 |
|---|---|---|---|---|---|---|
| copd | -3.6154 | 1085.6 | 0.0003136 | [ -0.12649160 ; -0.03749426 ] | 0.247 | 0.329 |
| chf | -4.7321 | 1153.9 | 2.50E-06 | [ -0.13987054 ; -0.05787928 ] | 0.186 | 0.284 |
| diabetes | -0.82594 | 988.38 | 0.409 | [ -0.06733532 ; ; 0.02744380 ] | 0.660 | 0.680 |
| asthma | -2.3564 | 1159.6 | 0.01862 | [ -0.064970219 ; -0.005933539 ] | 0.085 | 0.121 |
| behavioral_health | -2.1514 | 1026.3 | 0.03168 | [ -0.101808461 ; -0.004680507 ] | 0.358 | 0.411 |
| cancer | -1.5445 | 1025.9 | 0.1228 | [ -0.08487983 ; ; 0.01011231 ] | 0.327 | 0.364 |
| esrd | -4.2171 | 1774.2 | 2.60E-05 | [ -0.04129399 ; -0.01507668 ] | 0.009 | 0.037 |
| current_age | 3.6642 | 1091.9 | 0.00026 | [ 0.9357007 ; 3.0930648 ] | 76.473 | 74.459 |
| gender | -0.1163 | 1002.8 | 0.9074 | [ -0.05285964 ; 0.04694485 ] | 0.440 | 0.443 |
| black | -1.2771 | 1056.3 | 0.2018 | [ -0.06152854 ; 0.01301305 ] | 0.158 | 0.182 |
| hisp | -1.4404 | 1175.5 | 0.15 | [ -0.033082898 ; 0.005072028 ] | 0.033 | 0.047 |
| race_other | 0.96286 | 846.06 | 0.3359 | [ -0.006563725 ; 0.019204644 ] | 0.019 | 0.012 |
| copd_esrd | -3.4788 | 1307 | 0.0005203 | [ -0.01434797 ; -0.00400065 ] | 0 | 0.009 |
| chf_esrd | -2.6055 | 1693.7 | 0.009254 | [ -0.022405259 ; -0.003160263 ] | 0.006 | 0.018 |
| diabetes_esrd | -3.8555 | 1823.9 | 0.0001195 | [ -0.03197295 ; -0.01041215 ] | 0.006 | 0.027 |
| asthma_esrd | -2.836 | 1307 | 0.004638 | [ -0.010346999 ; -0.001885417 ] | 0 | 0.006 |
| behavioral_health_esrd | -3.088 | 1760.9 | 0.002047 | [ -0.025902186 ; -0.005779544 ] | 0.006 | 0.021 |
| cancer_esrd | -3.7604 | 1307 | 0.0001771 | [ -0.016287244 ; -0.005119484 ] | 0 | 0.011 |
| copd_cancer | -3.1217 | 1207.5 | 0.001841 | [ -0.07765330 ; -0.01771529 ] | 0.085 | 0.133 |
| chf_cancer | -1.4509 | 1113.9 | 0.1471 | [ -0.046371725 ; 0.006945446 ] | 0.071 | 0.090 |
| diabetes_cancer | -1.023 | 1032.7 | 0.3066 | [ -0.06424023 ; 0.02021261 ] | 0.223 | 0.245 |
| asthma_cancer | -3.0878 | 1428.3 | 0.002055 | [ -0.04557347 ; -0.01016459 ] | 0.024 | 0.052 |
| behavioral_health_cancer | -2.2963 | 1117 | 0.02184 | [ -0.075118882 ; -0.005895342 ] | 0.126 | 0.167 |
| copd_behavioral_health | -2.686 | 1126.2 | 0.007339 | [ -0.08523211 ; -0.01327401 ] | 0.137 | 0.187 |
| chf_behavioral_health | -2.8605 | 1119.5 | 0.004308 | [ -0.09300368 ; -0.01732635 ] | 0.156 | 0.211 |
| diabetes_behavioral_health | -2.0905 | 1046.7 | 0.03682 | [ -0.093779960 ; -0.002967329 ] | 0.273 | 0.321 |
| asthma_behavioral_health | -1.7038 | 1171.3 | 0.08869 | [ -0.041669239 ; 0.002935147 ] | 0.046 | 0.066 |
| copd_asthma | -2.5013 | 1222 | 0.0125 | [ -0.05620246 ; -0.00679221 ] | 0.056 | 0.087 |
| chf_asthma | -3.3257 | 1411.3 | 0.0009045 | [ -0.05247498 ; -0.01353808 ] | 0.030 | 0.063 |
| diabetes_asthma | -2.0522 | 1176.8 | 0.04037 | [ -0.051360690 ; -0.001154728 ] | 0.059 | 0.086 |
| copd_diabetes | -2.7073 | 1094.8 | 0.006889 | [ -0.09612953 ; -0.01534091 ] | 0.187 | 0.243 |
| chf_diabetes | -4.5494 | 1185.2 | 5.93E-06 | [ -0.1263140 ; -0.0501936 ] | 0.150 | 0.239 |
| copd_chf | -3.629 | 1227.9 | 0.0002963 | [ -0.08844561 ; -0.02637230 ] | 0.091 | 0.148 |

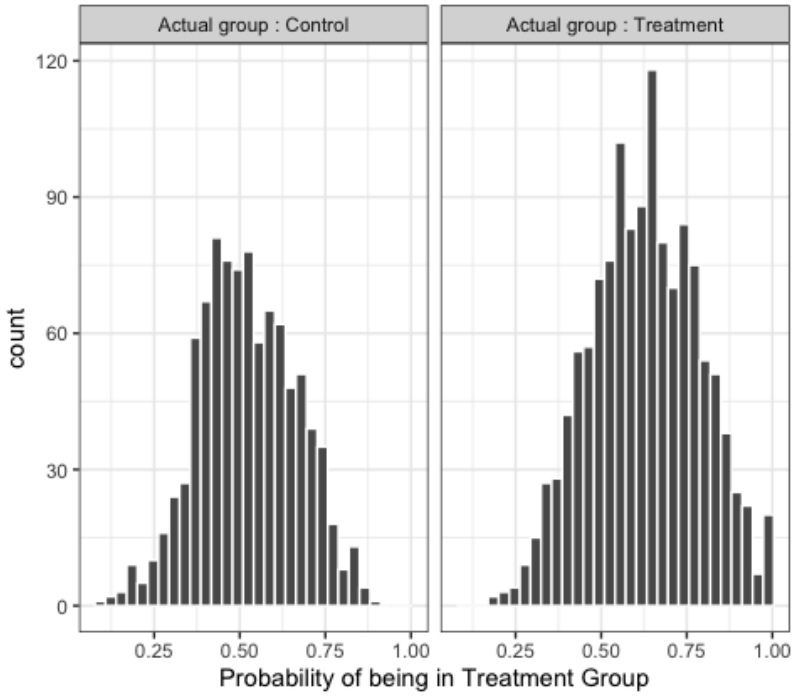
Note: Difference-in-means and t-tests; Observations in Group 1 belong to the control group, while observations in Group 2 received the intervention.

Table 2.7: Difference-in-means; t-tests (inverted groups)

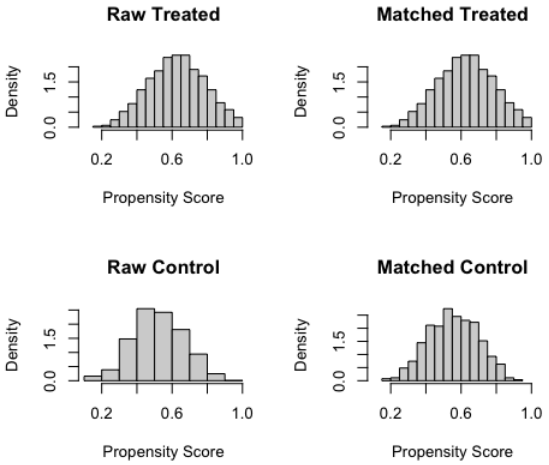
| Variable | t | df | p-value | 95% ; C.I. | Mean in Group 1 | Mean in Group 2 |
|---|---|---|---|---|---|---|
| copd | 1.371 | 1043.5 | 0.1707 | [ -0.01377382 ; 0.07765880 ] | 0.251 | 0.219 |
| chf | 1.1769 | 1033.5 | 0.2395 | [ -0.01603977 ; 0.06411563 ] | 0.177 | 0.153 |
| diabetes | -0.91576 | 1073.4 | 0.36 | [ -0.07600467 ; 0.02763513 ] | 0.617 | 0.641 |
| asthma | -1.0616 | 1165.1 | 0.2886 | [ -0.04524630 ; 0.01347308 ] | 0.076 | 0.092 |
| behavioral_health | 1.1302 | 1069.1 | 0.2586 | [ -0.02182649 ; 0.08112699 ] | 0.373 | 0.344 |
| cancer | -0.056267 | 1086.6 | 0.9551 | [ -0.05150214 ; 0.04863072 ] | 0.322 | 0.323 |
| esrd | -0.69667 | 1320 | 0.4861 | [ -0.009976549 ; 0.004747630 ] | 0.004 | 0.006 |
| current_age | -0.84968 | 1037.6 | 0.3957 | [ -1.6749436 ; 0.6627074 ] | 76.429 | 76.935 |
| gender | -0.50323 | 1088.8 | 0.6149 | [ -0.06668984 ; 0.03946439 ] | 0.429 | 0.442 |
| black | -0.96894 | 1128.5 | 0.3328 | [ -0.05939513 ; 0.02012522 ] | 0.158 | 0.178 |
| hisp | 0.48217 | 1020.8 | 0.6298 | [ -0.01394775 ; 0.02303514 ] | 0.032 | 0.028 |
| race_other | -0.10938 | 1102 | 0.9129 | [ -0.01768906 ; 0.01582101 ] | 0.025 | 0.026 |
| copd_esrd | NaN | NaN | NA | - | 0 | 0 |
| chf_esrd | -0.83046 | 1414.8 | 0.4064 | [ -0.007994722 ; 0.003238935 ] | 0.002 | 0.004 |
| diabetes_esrd | -0.83046 | 1414.8 | 0.4064 | [ -0.007994722 ; 0.003238935 ] | 0.002 | 0.004 |
| asthma_esrd | NaN | NaN | NA | - | 0 | 0 |
| behavioral_health_esrd | -0.83046 | 1414.8 | 0.4064 | [ -0.007994722 ; 0.003238935 ] | 0.002 | 0.004 |
| cancer_esrd | NaN | NaN | NA | - | 0 | 0 |
| copd_cancer | 0.84135 | 1022.5 | 0.4003 | [ -0.01688372 ; 0.04222889 ] | 0.088 | 0.075 |
| chf_cancer | -0.26351 | 1108.8 | 0.7922 | [ -0.02976357 ; 0.02271554 ] | 0.063 | 0.066 |
| diabetes_cancer | -0.61581 | 1108.4 | 0.5381 | [ -0.05619166 ; 0.02934553 ] | 0.194 | 0.208 |
| asthma_cancer | -0.57785 | 1186.5 | 0.5635 | [ -0.01876961 ; 0.01022877 ] | 0.017 | 0.021 |
| behavioral_health_cancer | 0.34984 | 1067 | 0.7265 | [ -0.03005829 ; 0.04310203 ] | 0.137 | 0.131 |
| copd_behavioral_health | 1.5004 | 1008 | 0.1338 | [ -0.00875028 ; 0.06559131 ] | 0.150 | 0.122 |
| chf_behavioral_health | 1.077 | 1031.4 | 0.2817 | [ -0.01700721 ; 0.05838582 ] | 0.152 | 0.132 |
| diabetes_behavioral_health | 0.68345 | 1067.5 | 0.4945 | [ -0.03085737 ; 0.06384198 ] | 0.272 | 0.256 |
| asthma_behavioral_health | -0.0078457 | 1086.4 | 0.9937 | [ -0.02201883 ; 0.02184344 ] | 0.044 | 0.044 |
| copd_asthma | -0.44496 | 1128.4 | 0.6564 | [ -0.03003987 ; 0.01893352 ] | 0.053 | 0.059 |
| chf_asthma | 0.07839 | 1072.5 | 0.9375 | [ -0.01465335 ; 0.01587289 ] | 0.021 | 0.020 |
| diabetes_asthma | -0.62117 | 1143.5 | 0.5346 | [ -0.03298240 ; 0.01712026 ] | 0.055 | 0.063 |
| copd_diabetes | 0.46447 | 1065.3 | 0.6424 | [ -0.03070396 ; 0.04974750 ] | 0.173 | 0.164 |
| chf_diabetes | 1.1541 | 1022.9 | 0.2487 | [ -0.01489883 ; 0.05744803 ] | 0.139 | 0.118 |
| copd_chf | 1.2547 | 991.49 | 0.2099 | [ -0.01063671 ; 0.04835671 ] | 0.090 | 0.071 |

Note: Difference-in-means and t-tests for inverted groups; Observations in Group 1 received the intervention, while observations in Group 2 are part of the control group.

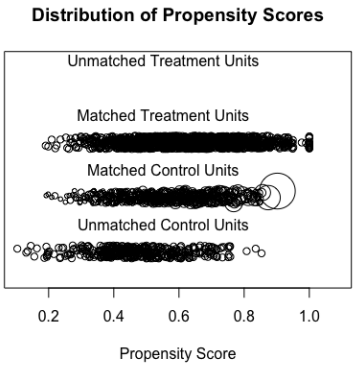
Figure 2.1: Propensity score matching




Estimated propensity scores by treatment status

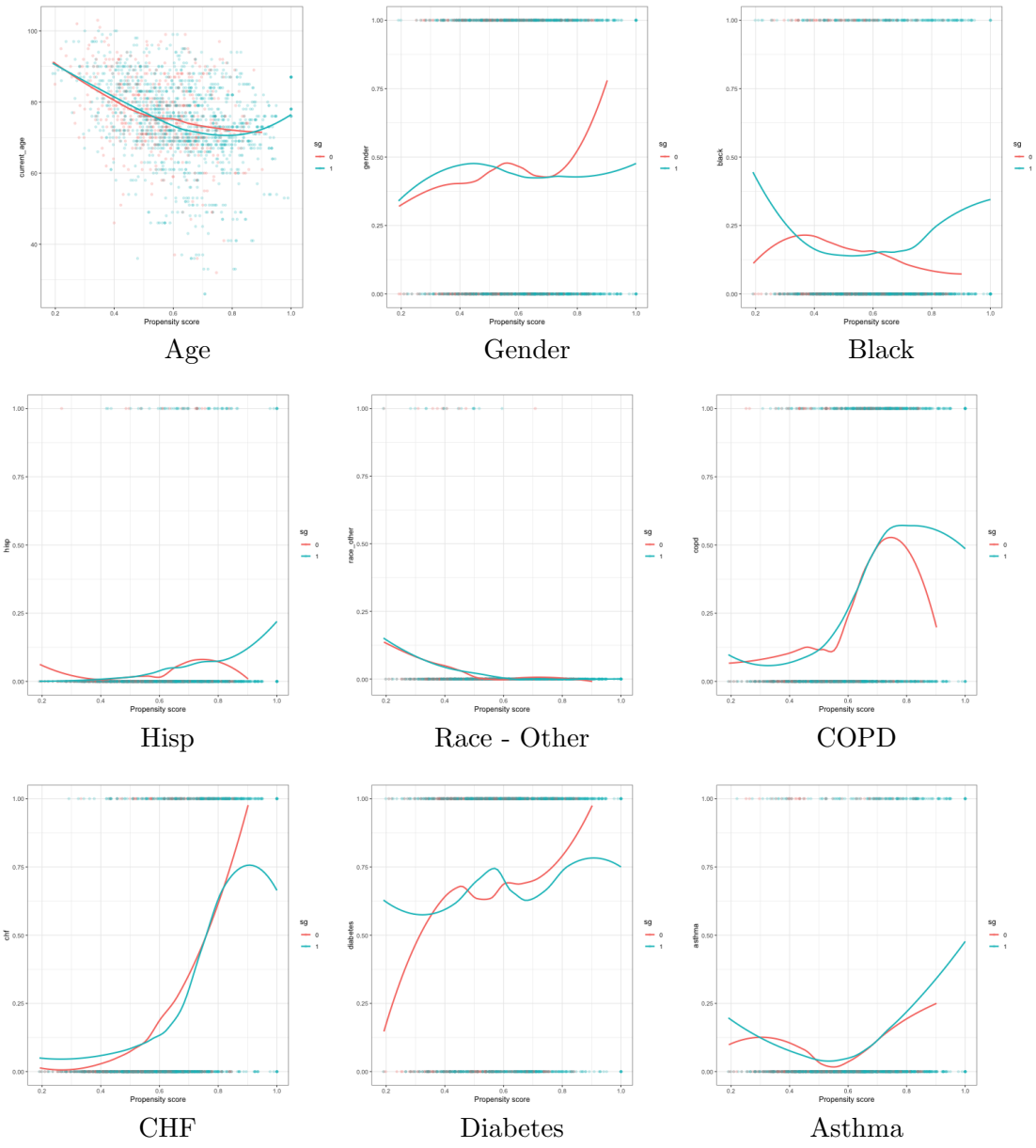



Propensity score - Raw vs Matched




Region of common support

Figure 2.2: Covariate balance plots

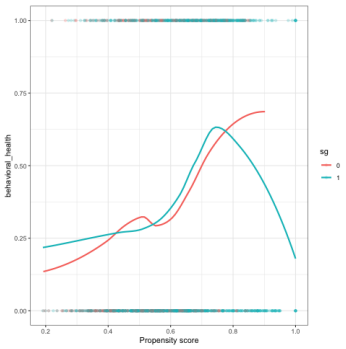



Age | Gender | Black

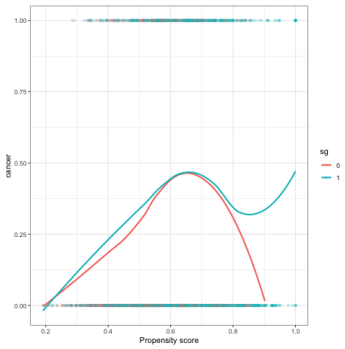
Hisp | Race - Other | COPD

CHF | Diabetes | Asthma

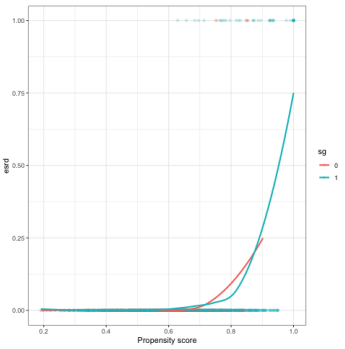
Figure 2.2 (continued)



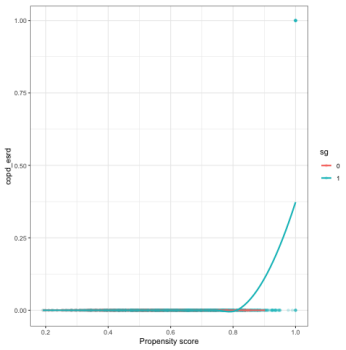

Behavioral health



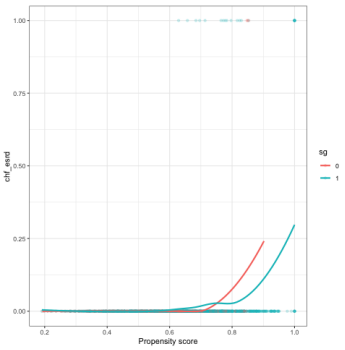

Cancer



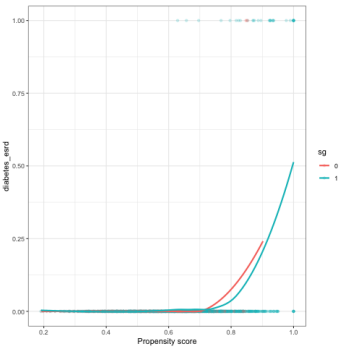

ESRD



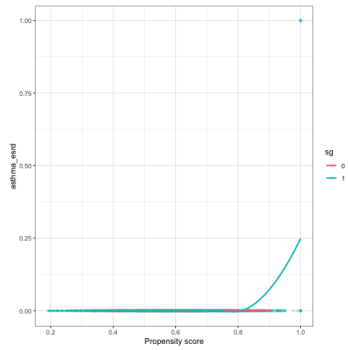

COPD - ESRD



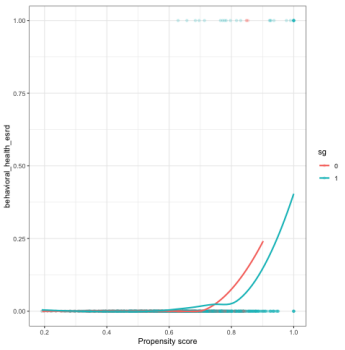

CHF - ESRD



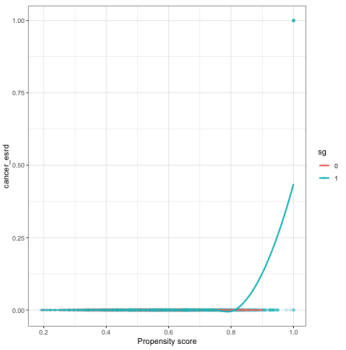

Diabetes - ESRD




Asthma - ESRD

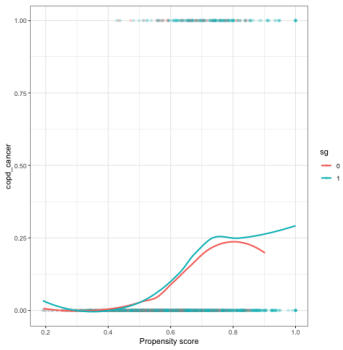



Behav Health - ESRD

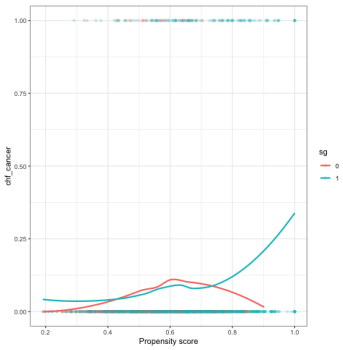



Cancer - ESRD

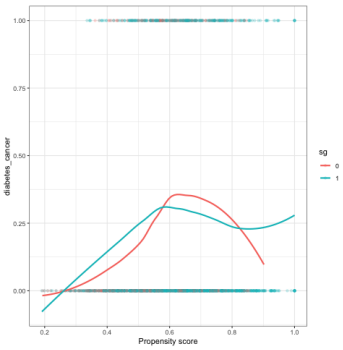
Figure 2.2 (continued)



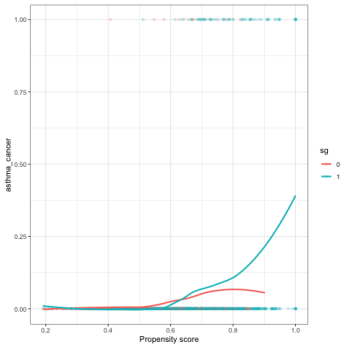

COPD - Cancer



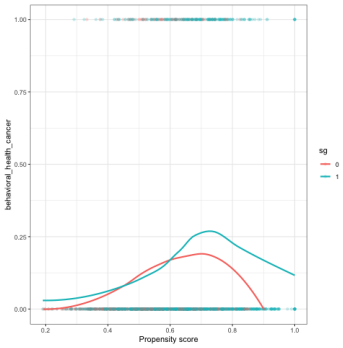

CHF - Cancer



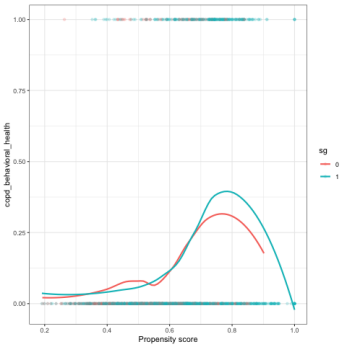

Diabetes - Cancer



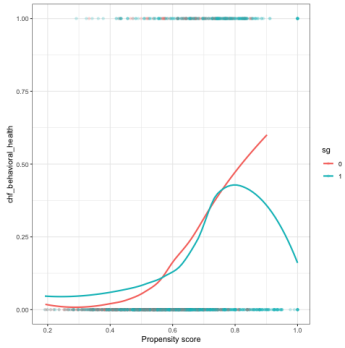

Asthma - Cancer



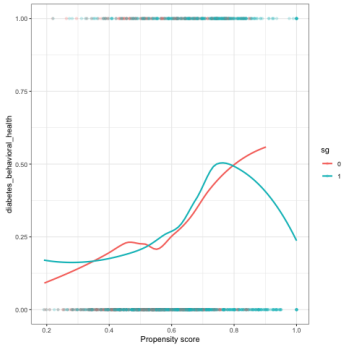

Behav health - Cancer



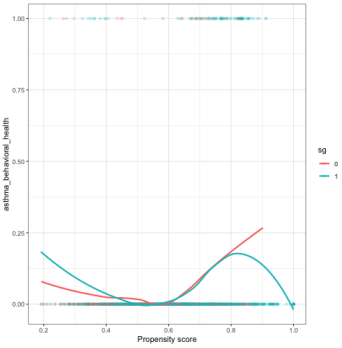

COPD - Behav health




CHF - Behav health

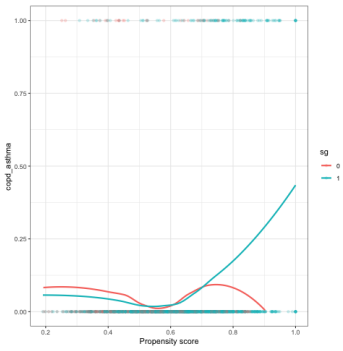



Diabetes - Behav health

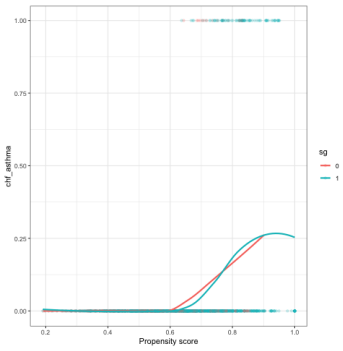



Asthma - Behav health

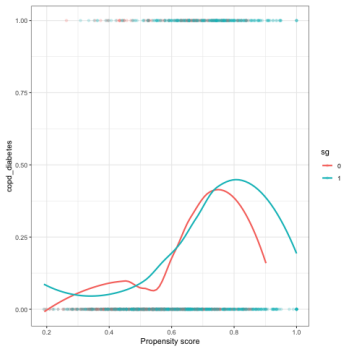
Figure 2.2 (continued)



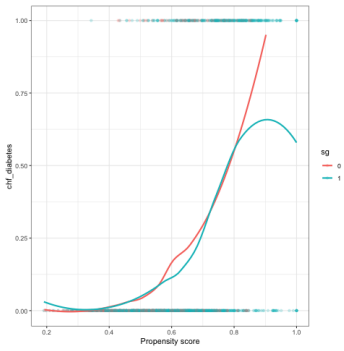

COPD - Asthma



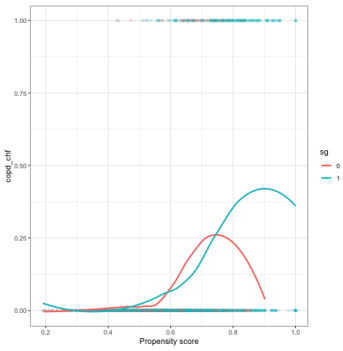

CHF - Asthma




COPD - Diabetes




CHF - Diabetes




COPD - CHF

Figure 2.3: Propensity score matching, inverted groups

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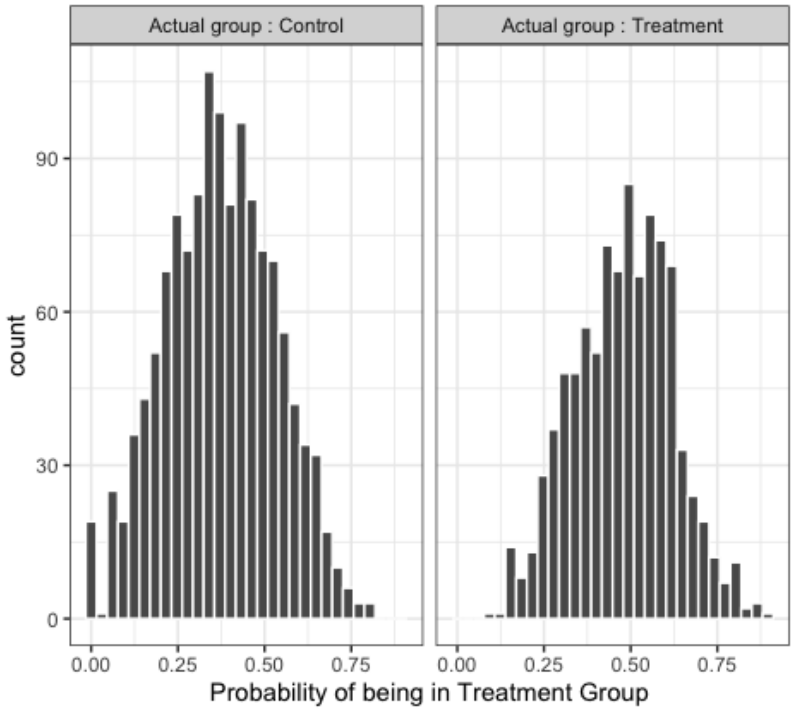
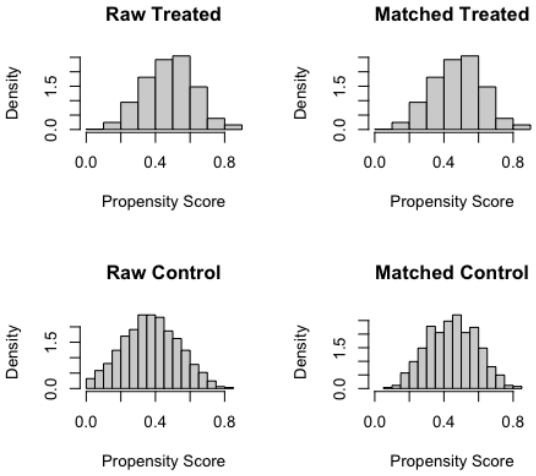
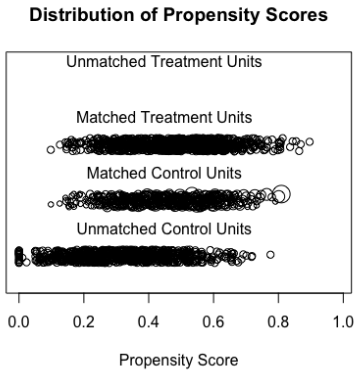



Estimated propensity scores by treatment status

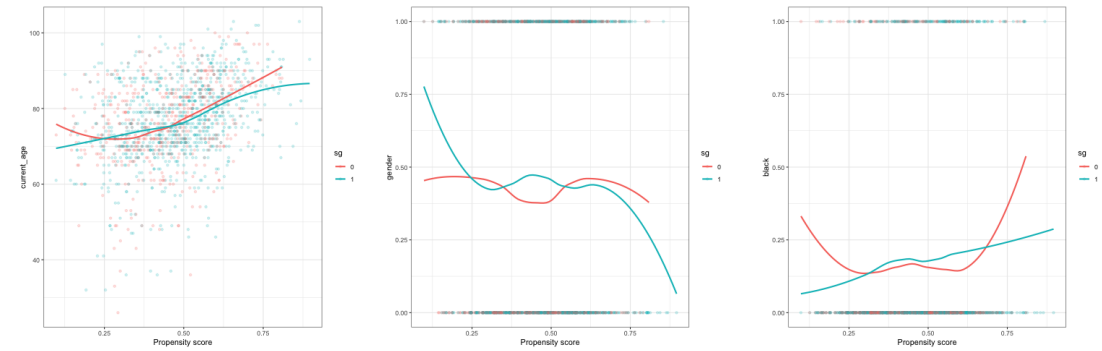



Propensity score - Raw vs Matched

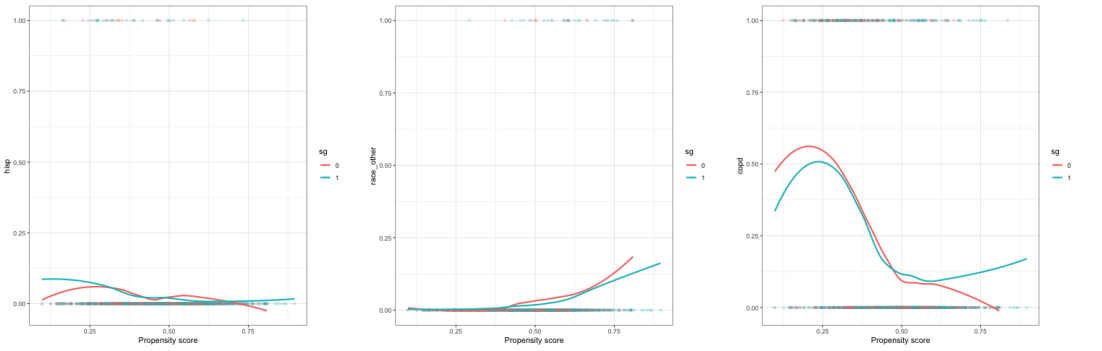



Region of common support

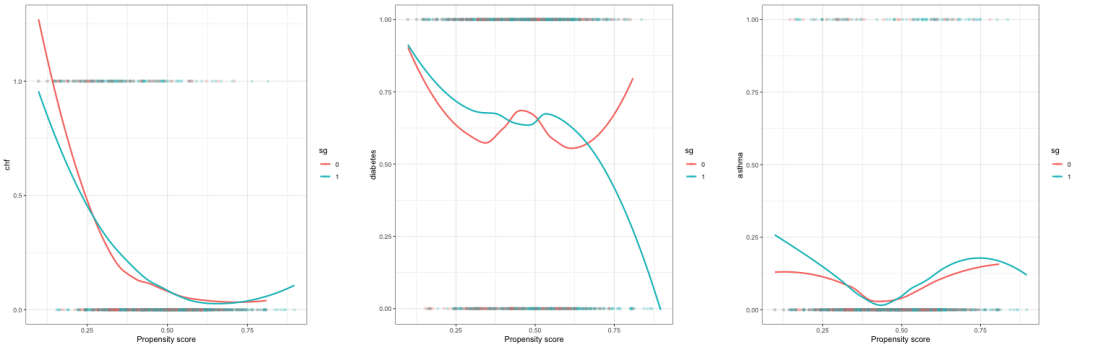
Figure 2.4: Covariate balance plots, inverted groups




Age Gender Black

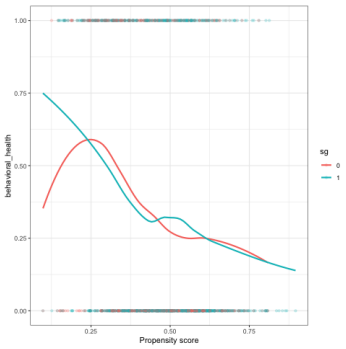



Hisp Race - Other COPD

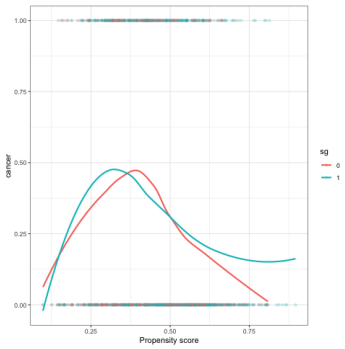



CHF Diabetes Asthma

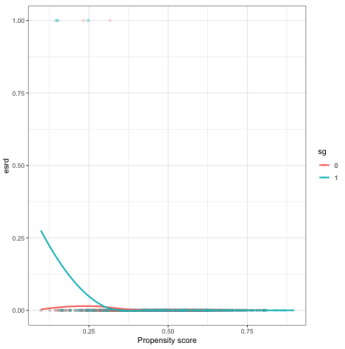
Figure 2.4 (continued)



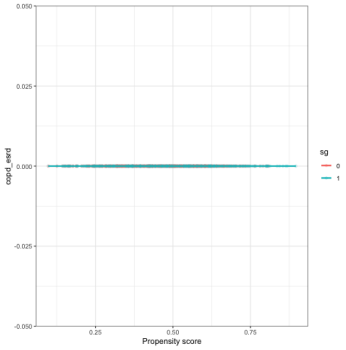

Behavioral health



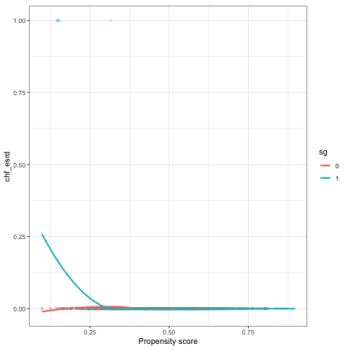

Cancer



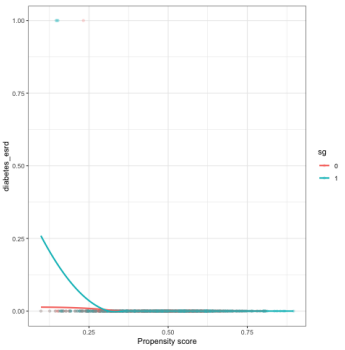

ESRD



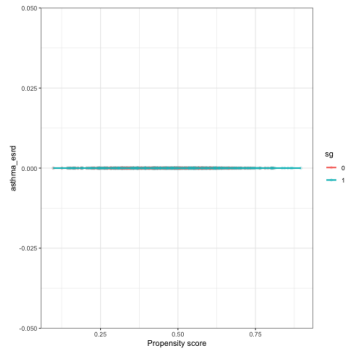

COPD - ESRD



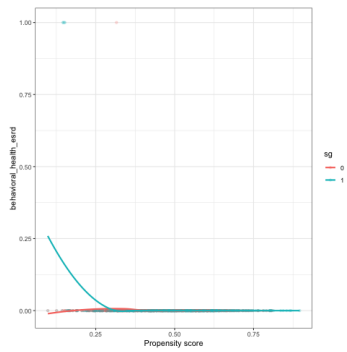

CHF - ESRD



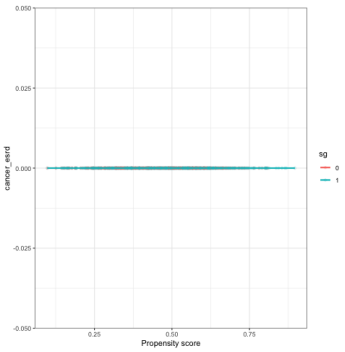

Diabetes - ESRD




Asthma - ESRD

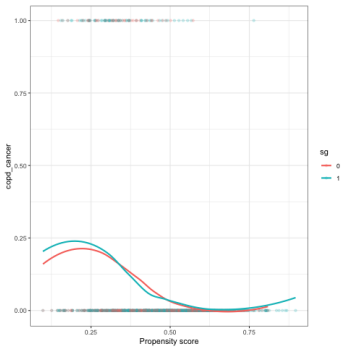



Behav health - ESRD

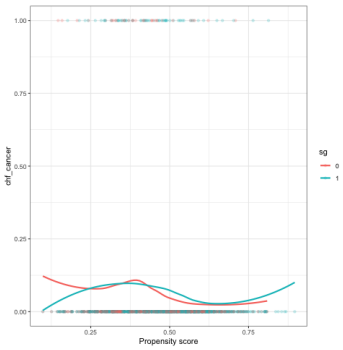



Cancer - ESRD

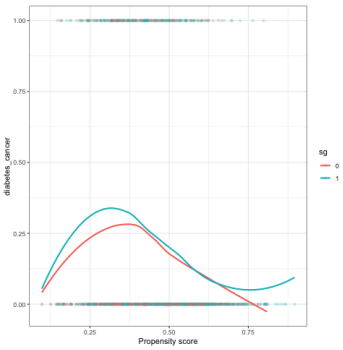
Figure 2.4 (continued)



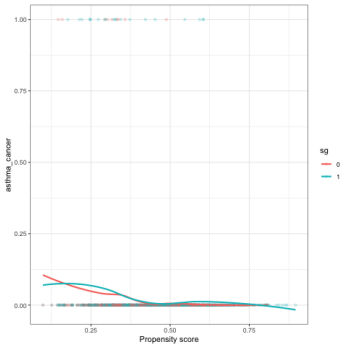

COPD - Cancer



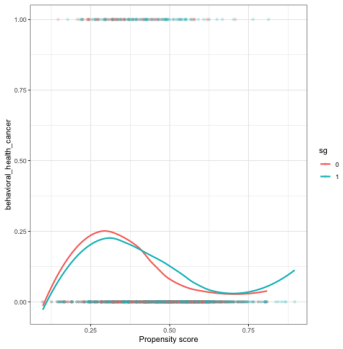

CHF - Cancer



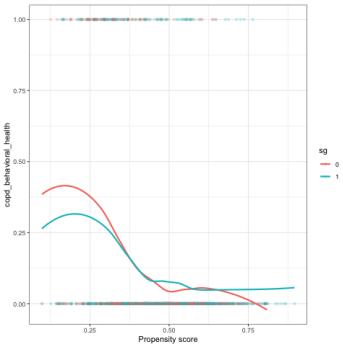

Diabetes - Cancer



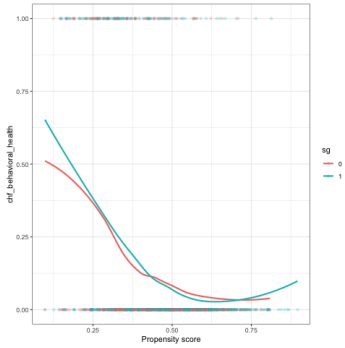

Asthma - Cancer



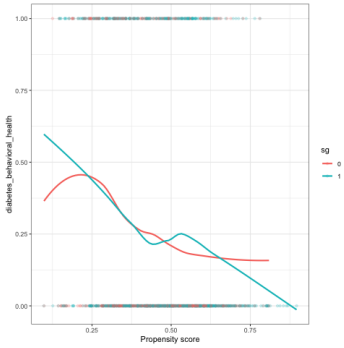

Behav health - Cancer



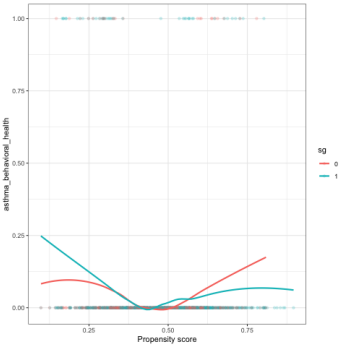

COPD - Behav health




CHF - Behav health

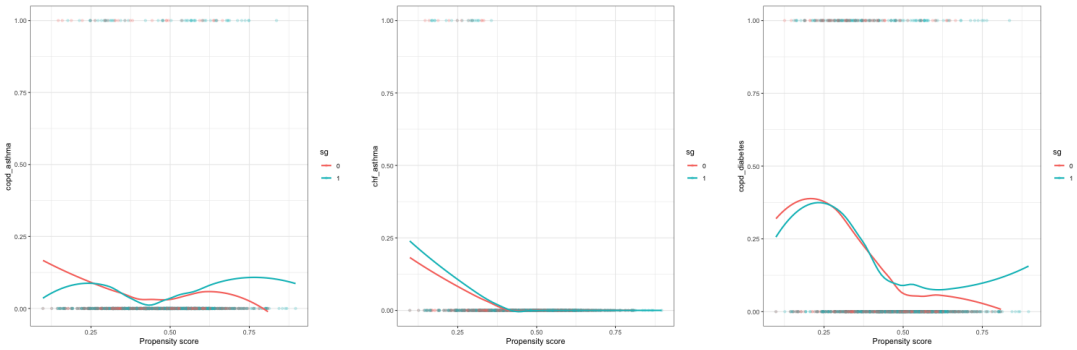



Diabetes - Behav health

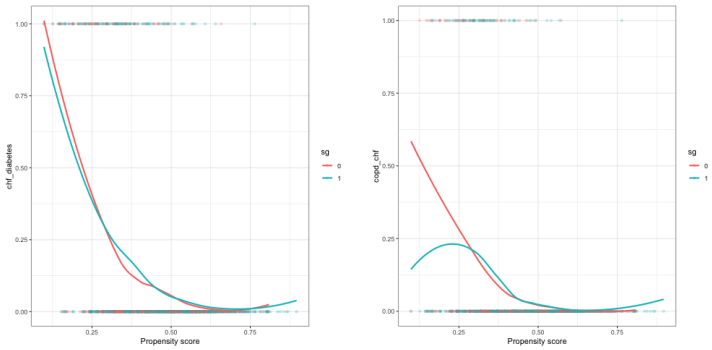



Asthma - Behav health

Figure 2.4 (continued)




COPD - Asthma CHF - Asthma COPD - Diabetes




CHF - Diabetes COPD - CHF

CHAPTER 3

# SMOKING CESSATION: LEVERAGING WILLINGNESS-TO-ACCEPT TO TARGET INTERVENTIONS

## 3.1 Introduction

Smoking during pregnancy is a widely documented preventable cause of adverse maternal and child health outcomes. Maternal smoking in pregnancy increases the risk of experiencing cardiovascular events such as stroke (James, Bushnell, Jamison, and Myers (2005)), acute myocardial infarction (James, Jamison, Biswas, Brancazio, Swamy, and Myers (2006), and venous thromboembolism (Heit, Kobbervig, James, Petterson, Bailey, and Melton III (2005)). An increased risk of cervical (Yang, Jin, Nakao, Rahimtula, M. M. Pater, and A. Pater (1996)) and breast (Burton and Sulaiman (2000)) cancer has been documented as well. Additionally, pregnant smokers are also more likely to have more comorbidities (Roelands, Jamison, Lyerly, and James (2009)). Adverse effects that impact the child include a three-fold increase in the likelihood of sudden infant death syndrome (T. M. Anderson, Lavista Ferres, Ren, Moon, Goldstein, Ramirez, and Mitchell (2019), Centers for Disease Control and Prevention (2010))), brain and lung tissue damage in the fetus, lower birth weight, and premature delivery (Centers for Disease Control and Prevention (2010)). Even though the smoking rate decreases once women become pregnant, approximately 7.2% continue smoking (Drake, Driscoll, and Mathews (2018)).

While the adverse effects on one's health are known, an endogenous motivation to quit may not be sufficient. Large-scale public health campaigns have shown that an increase in quit attempts can be achieved (Brown, Kotz, Michie, Stapleton, Walmsley,

and West (2014)), bridging the gap between the intention to quit and an actual quit attempt. However, another study found that while as many as 69% of smokers in 2010 reported that they would like to quit, with more than half of them having attempted to quit in the prior year, only 6% were successful (Malarcher, Dube, Shaw, Babb, and Kaufmann (2011)).

To maximize the effect of public health campaigns, it is important not only to efficiently target interventions for smoking cessation but also understand the underlying behavior driving intention to quit and the strength of smokers' preferences. Smoking is a self-control problem with present-biased preferences. Smokers place too much weight on present costs and benefits, and too little weight on future costs and benefits, resulting in over-consumption of the leisure good in pursuit of immediate gratification (Levy, Mohlman, and Zhang (2015)). Better understanding of individuals' pricing of immediate and future costs and benefits may enable the use of monetary incentives to influence how smokers revise their plans.

Monetary incentives delivered to GPs tied to the number of abstinent patients in their panel was not effective when compared to the usual course of treatment for smoking cessation, even when the intervention was paired with GP training on the latest smoking cessation treatments available. When cost-free medication was added, the intervention was cost-effective (Salize, Merkel, Reinhard, Twardella, Mann, and Brenner (2009)). Reducing total quitting costs for the individual by eliminating the cost of treatment was shown to be effective, showing that monetary incentives delivered to smokers as opposed to intermediaries can increase quit rates.

Willingness to pay for smoking cessation treatments has often been explored to better understand how individuals assign their price for quitting. A study exploring the relationship between willingness to use smoking cessation products and the willingness to pay for that product concluded that out of the 52% of individuals willing to use nicotine replacement treatment products, only half are willing to pay for treatment (Aumann, Treskova, Hagemann, and von der Schulenburg (2016)).

Monetary incentives have also been shown to be effective, not only when they are delivered to smokers, but also when used as a commitment device (Russell, Volpp, Kwong, Cosgriff, Harhay, Zhu, and Halpern (2021)). This paper further explores data from a trial performed by the Indiana University (Middlestadt, Macy, Arrieta, and Jay (2020)) and approved by its Institutional Review Board. Our objective is to explore whether individuals willing to accept a monetary incentive for smoking cessation exhibit increased quit rates, and also the role of a subsequent delivery of a monetary incentive plays as a strengthen mechanism or commitment device that increases quit rates.

The remainder of this chapter is organized as follows: Section Literature review is a review of the relevant literature. In section Program design, we describe the program design implementation details. In section Methods, we describe the empirical methods used. In section Results, we discuss the results of our estimation. Lastly, in section Conclusion we provide concluding remarks.

## 3.2 Literature review

Smoking during pregnancy is a preventable cause of adverse health and birth outcomes in the US. An analysis of birth certificates performed by the Centers for Disease

Control and Prevention (CDC) to identify state-specific trends shows that approximately one in 14 women has reported smoking during their pregnancy, which comes to an average prevalence of 7.2% that varies by state and in some cases exceeds 20% (Drake et al. (2018). The 2016 analysis carried out by the CDC represents a reduced prevalence when compared to the 2003 analysis, which showed an average prevalence of 11% (Mathews and Rivera (2004)). Among the three largest Hispanic-origin and race groups used in the study, non-Hispanic American Indian or Alaska Natives had the highest prevalence of maternal smoking (16.7%), approximately 1.6 times as likely to engage in smoking during pregnancy as non-Hispanic white women. Non-Hispanic white women had the second-highest prevalence (10.5%), followed by non-Hispanic Black women (6.0%).

Smoking during pregnancy carries an increased risk of acquiring other conditions that present a further risk for adverse health outcomes for both the mother and the child. An analysis of the Nationwide Inpatient Sample dataset produced by the Healthcare Cost and Utilization Project of the Agency for Healthcare Research and Quality showed 34.2 per 100,000 deliveries included a diagnosis of stroke -a cardiovascular event for which smoking is a significant risk factor with odds-ratio of 1.9- on pregnancy-related hospital discharges during the years 2000 and 2001 (James et al. (2005)). The reduced function and potential disability resulting from a pregnancy-related stroke during puerperium can further pose risks to the newborn.

A study using the Nationwide Inpatient Sample for the years 2000 to 2002 shows that acute myocardial infarction is another condition that can occur as a consequence of the increased risk posed by smoking, with a rate of 6.2 per 100,000 deliveries having included the diagnosis during discharge, and a case fatality rate of 5.1% (James et

al. (2006)). Other cardiovascular events with an increased odds ratio due to smoking are deep vein thrombosis, pulmonary embolism, and myocardial infarction (Roelands et al. (2009)).In addition to cardiovascular events, smoking during pregnancy presents an increased risk of cancer to the mother. Studies show that active smokers have an increased likelihood of developing breast cancer (Burton et al. (2000), Lash and Aschengrau (1999)). Passive smokers are also at an increased risk when compared to groups never exposed actively or passively (Morabia, Bemstein, Heritier, and Khatchatrian (1996), Johnson, Hu, and Mao (2000)). Lastly, cigarette smokers have a risk of developing cervical cancer that increases with the number of cigarettes smoked and the years spent as a smoker (Yang et al. (1996)). The different forms of cancer and the cardiovascular events for which smokers are at an increased risk of developing are just part of the adverse effects since smokers are also more likely to have experienced pneumonia, bronchitis, or influenza, as well as other comorbidities (Roelands et al. (2009)). Naturally, the adverse health effects of smoking in pregnancy do not only impact the mother but also have an impact on the child. The increased likelihood of sudden infant death syndrome is three-fold (T. M. Anderson et al. (2019), Centers for Disease Control and Prevention (2010)), and brain and lung tissue damage in the fetus, lower birth weight, and premature delivery are also linked to cigarette smoking (Centers for Disease Control and Prevention (2010)). Miscarriage, placental abruption, stillbirth, low birth weight, and neonatal mortality are other risk factors originating from smoking during pregnancy (McDonnell and Regan (2019)).

The literature not only widely documents the prevalence of smoking during pregnancy and its impact on adverse health effects, but it also studies large-scale public health campaigns targeting smoking cessation. Results from these campaigns have

been mixed with different approaches and targets achieving different levels of efficacy. When leveraging the smokers' intention to quit, a study showed that while 69% of smokers in 2010 reported an intention to quit, only 6% of the smokers were successful in doing so (Malarcher et al. (2011)). Years later, a campaign intended to bridge the gap between the intention to quit and the actual attempt produced positive results and proved to be successful (Brown et al. (2014)). These results indicate that targeting interventions for smoking cessation by leveraging participants' intention to quit requires a deeper understanding of the link between smokers' willingness to quit smoking and the time consistency of their preferences relative to smoking since this may influence the analysis.

Smoking is a self-control problem with present-biased preferences. Present costs and benefits carry a higher weight, and future costs and benefits have a reduced weight. This combination leads to seeking gratification in the short term through excessive consumption of leisure goods in the present period (Levy et al. (2015)). Pricing of both immediate and future costs and benefits allows for the implementation of monetary incentives that can influence these weights and how smokers revise their plans.

Identifying the delivery mechanism for the monetary incentive is also critically important, as it can lead to varying levels of effectiveness and quit rates. Primary care-based strategies to increase quit rates call for three main delivery channels: incentive delivery to the physician, to the patient, or a combination of both. A study explored the effectiveness of each channel (Salize et al. (2009)). When the delivery channel was the physician, the study linked the number of abstinent patients in the physician's panel to the incentive delivered to the GP. When the delivery mechanism centered

around the patient, the study used a combination of cost-free nicotine replacement medication and physician training. Lastly, the study combined the two channels. The study found that delivering the incentive directly to the GP was ineffective in comparison to the usual smoking cessation treatment. Pairing the incentive with physician education on the latest smoking cessation treatments available did not make a difference. However, adding cost-free medication to the intervention proved to be effective. These results show that reducing the total quitting costs for the individual is effective in increasing smoking cessation rates, confirming that monetary incentives delivered directly to smokers help offset the immediate costs and positively affect quit rates. This paper shares similarities with Salize, Merkel, Reinhard, Twardella, Mann, and Brenner (2009) in that the monetary incentive is delivered directly to the participant.

Exploring willingness to pay for smoking cessation treatments can also help to better understand individuals' pricing of the costs and benefits associated with quitting. Aumann et al. (2016) (Aumann et al. (2016)) explored the relationship between willingness to pay for smoking cessation products and willingness to use them and found that while 52% of the individuals were willing to use nicotine replacement products, only half of them were willing to actually pay for that treatment. This expressed a preference against out-of-pocket costs provides economic intuition behind the weight of the costs associated with smoking cessation. The difference with our paper lies in that we explore WTA as opposed to WTP or WTU effects.

Given the preference against out-of-pocket costs, using monetary incentives delivered to individuals could then significantly offset these costs: monetary incentives can be effective not only when they are delivered to the smokers themselves, but also when leveraged as a commitment device (Russell, Volpp, Kwong, Cosgriff, Harhay, Zhu,

and Halpern). Russell, Volpp, Kwong, Cosgriff, Harhay, Zhu, and Halpern (2021) found that an $800 incentive for smoking cessation paid at six months, combined with a baseline deposit of $150 made by the smoker can be used to implement a cost-effective and efficient smoking cessation program. Our paper shares similarities with Russell, Volpp, Kwong, Cosgriff, Harhay, Zhu, and Halpern (2021) in that we explore the role of the monetary incentive as a commitment component.

## 3.3 Program design

We analyze data obtained from a study performed by the Indiana University and approved by its institutional review board (Middlestadt et al. (2020)). Participants were recruited from 11 prenatal clinics located in Indiana (five in central Indiana, four in northwest Indiana, and two in south-central Indiana), where the staff at each clinic identified the eligible women and obtained authorization compliant with the Health Information Portability and Accountability Act (HIPAA). Eligibility was determined by administering an initial screening questionnaire that recorded demographics characteristics, willingness to participate in the study and signature of the HIPAA authorization form, whether the individual reported having smoked in the past 30 days, details regarding the pregnancy, use of illicit drugs, and medications being used. Additionally, the initial screening questionnaire recorded the baseline urine cotinine test result. Eligibility was determined by identifying women who both were in the first 20 weeks of pregnancy and who have reported smoking in the past 30 days. Individuals with a high-risk pregnancy, younger than 18 years old, incarcerated, or those who reported use of illicit drugs, antipsychotic medication, or opioid substitution medication were deemed ineligible to participate and thus excluded from the study. Individuals planning to leave the area in the six-month postpartum period were also excluded from the study. Once the eligible women were identified and

enrolled in the program, they were referred to the research staff which proceeded to obtain informed consent and administered an intake form and a baseline survey.

The program was composed of a control group, and two experimental groups ("low incentive" and "high incentive"). All three groups of participants were offered a $20 CVS gift card baseline incentive. The two experimental groups received an additional $25 ("low incentive" group) or $50 ("high incentive group") respectively for each prenatal office visit where the participant reported abstinence. During each visit, a urine sample was taken and, unknown to the participants, cotinine levels were measured. The additional incentive (either $25 for the "low incentive" group, or $50 for the "high incentive" group) were not conditional on the urine cotinine test results: reporting not having smoked in the past 30 days was sufficient to receive the incentive, and at no point were the participants made aware of the cotinine test results.

After enrollment in the program, a baseline questionnaire was administered, capturing individuals' perceived norms regarding smoking, taking prenatal vitamins, drinking alcohol, and going to prenatal care appointments. The baseline questionnaire also captured the individual's intention to quit and household characteristics. Of particular interest to this study, the baseline questionnaire also captured the individuals' willingness to accept a cash incentive to quit smoking. The question was phrased as *"Would you be willing to quit smoking for a cash incentive of$10 per month, during the next nine months?"* with only two options (yes or no) as possible answers.

During each prenatal care office visit, a questionnaire was administered to each participant, where the date of the visit and the urine cotinine test result were recorded. The visit questionnaire captured the self-reported consumption of nicotine in the 30-

day period leading to the visit, as well as consumption of heavy alcohol use or illicit drugs. Information regarding any incentive payments made during that visit such as the gift card number and the amount paid were also recorded in the same questionnaire, as captured by either the clinic staff during the visit or by contacting the participant by phone later.

Postpartum data from medical records was captured for each participant, recording birth outcome data points for the delivery, such as physiological data for the newborn, diagnosis information for any complications during delivery, Apgar test results, and the associated length of stay for both the mother and the newborn, inclusive of whether neonatal intensive care unit (NICU) days were necessary.

Finally, a postpartum questionnaire was administered, recording perceived norms surrounding smoking, taking prenatal vitamins, drinking alcohol, and attending prenatal care appointments, as well as details about nicotine consumption.

## 3.4 Data

The de-identified and non-coded data used in this study was collected through questionnaires administered at different points in the study. The clinical initial screening survey consisted of 33 questions that recorded participant demographics, gestational age and other characteristics of the pregnancy, self-reported use of nicotine and medications, incarceration status, and HIPAA authorization status. Responses to this questionnaire were used to determine program eligibility. An intake and enrollment form and a baseline questionnaire were then administered either on paper or during a subsequent phone call to capture additional data elements surrounding the individual's attitudes towards smoking and her household environment characteristics. On the baseline questionnaire, the question regarding the individual's willingness to accept (*"Would you be willing to quit smoking for a cash incentive of$10 per month, during the next nine months?"*) presented "Yes" and "No" as possible answers and was coded in the data set as 1 and 0 respectively.

Additional data points recorded at each visit include the urine cotinine test results for each visit, the participants' self-reported smoking habits in the 30 days, self-reported consumption of other non-cigarette forms of nicotine (e.g., nicotine patch, e-cigarettes, lozenges, or gum), and use of medication and illicit drugs. Any payments made to the participants after reporting not having smoked in the past 30 days were also part of the data set.

Of the 511 women referred to clinic staff for enrollment, only 392 met the eligibility criteria, and 333 were enrolled in the study: 113 in the control group, 109 in the low incentive group, and 111 in the high incentive group. The average age for women in either group and across groups was 26 years old (Table 3.1).

The majority of the eligible pregnant smokers analyzed in this study identified themselves as non-Hispanic (97%), the biggest race group being white (66%) as can be seen in Table 3.2. The second biggest group was Black/African American (29%).

Approximately 71% of the women in the study reported being single (Table 3.3), 65% of whom had not been able to attain a college degree as shown in Table 3.4. Single, divorced, or separated women comprise 77.6% of the sample, versus 22.4% for married or having a domestic partner.

The age range was 18 to 41 years old, with a mean age of 26 years old (Table 3.5). Approximately 84% of the women reported a low household income, 62% of those not exceeding $20,000 per year, and 22% not exceeding $35,000 per year (Table 3.6).

Table 3.7 shows that approximately one-fourth of the participants (23.2%) have not graduated from high school. Women who are neither married nor have a domestic partner, have an income below $35,000 per year, and have an educational level below college represent 65% of the sample. Of this subgroup of 161 women, one-third are Black, and two-thirds are white. Across study groups, 52 of these women are in the control group, 56 in the low incentive treatment arm, and 53 in the high incentive treatment arm.

When participants were asked whether they would accept a monthly payment to quit smoking, the acceptance rate was consistent for each group and for each group as a whole. Out of 261 recorded responses, 218 participants answered yes (83.5%) and 43 answered no (16.5%). The proportion of participants responding affirmatively to the question was 83.7% (n=72), 83.5% (n=71), and 83.5% (n=75) for the control, low incentive, and high incentive groups respectively, as seen in Figure 3.1.

## 3.5 Methods

Nicotine stays in the body for a few hours after exposure, and it has a half-life of approximately an hour or two (Hukkanen, Pleyton Jacob, and Benowitz (2005). Benowitz, Hukkanen, and Peyton Jacob (2009)). Approximately 0.031 milligrams out of 1 milligram of inhaled nicotine remains in the body six hours after smoking a cigarette, making it an ineffective indicator to measure nicotine consumption. Nicotine absorbed by the body is broken down by enzymes in the liver and produces the metabolite cotinine, which is excreted into the urine. The increased half-life of cotinine allows for testing for its presence during an increased time window that spans from one to 10 days.

Consistent with Middlestadt, Macy, Arrieta, and Jay (2020), to measure quit rates we defined smoking cessation as a measured urine cotinine level of 3 nanograms per milliliter (ng/mL) or lower during an office visit. For each visit, a dummy variable has been used to flag those visits where the urine cotinine level is below the 3ng/mL. The dummy variable was then used to calculate the percentage of office visits attended where the urine cotinine level measured was below the threshold.

We interacted a categorical variable identifying the experimental group with individuals' responses in the baseline questionnaire regarding their willingness to quit smoking in return for a cash incentive of $10 per prenatal visit.

The relationship between WTA and quit rate was estimated applying a linear regression model of the form:

$$PCTVUT_{it} = \beta_0 + \beta_1(Group_{it} \text{ x } WTA_{it}) + \beta_2 Demo_{it} + \epsilon_{it} \tag{3.1}$$

where $PCTVUT_{it}$ is the percent of office visits that the participant attended where the urine cotinine levels were below 3 ng/mL, $Group_{it}$ is the treatment arm (coded as 0 for the control group, 1 for the low incentive group, and 2 for the high incentive group), $WTA_{it}$ is an indicator for willingness to accept that takes the value of 1 if the individual is willing to accept a payment to stop smoking, $Demo_{it}$ is a vector of demographic controls inclusive of race, ethnicity, income, and age, and $\epsilon_{it}$ is the error term.

## 3.6 Results

Results from the main model specification can be seen in Table 3.8. Participants who provided an affirmative response to the question regarding their willingness to accept a monetary incentive in order to quit had exhibited urine cotinine levels below the threshold in 20% more office visits (on average) for both the low incentive and high incentive groups. This average increase is statistically significant, providing strong

evidence regarding the effectiveness of these incentives. This average increase is not observed for the control group participants who answered the question affirmatively. This fact highlights that an affirmative answer alone is not associated with a higher average number of visits with urine cotinine levels below the threshold, as only those that answered affirmatively and received payment exhibit this feature.

A simplified regression model shows that in the absence of controls, participants who share a willingness to accept monetary incentives in both treatment arms exhibit an increase in quit rates of 20.7% and 18.9% for the low and high incentive groups respectively (Table 3.9, regression 1). The observed increases are statistically significant at the 0.001 level. The magnitude change represents a 0.1% reduction when compared to the estimator obtained in the main regression model for the low incentive group, with a greater attenuation effect on the estimator for the high incentive group where it is reduced by 1.1%. In the context of quit rates during prenatal visits, this dampening effect is negligible.

Adding a constant term (Table 3.9, regression 3) to the main regression model to force the residual mean to equal zero and ensure in-sample errors are unbiased, we observe that the parameter estimates are consistent in magnitude and statistical significance. The standard errors for the parameters of interest increase slightly, but estimates remain statistically significant at the .001 level.

The incremental inclusion of a control variable for the participants' age in the model yields estimates of 20.3% and 19.2% average increase in office visits where urine cotinine levels were below the cut-off for both the low incentive and high incentive groups respectively (Table 3.9, regression 4). Both of these estimates are significant

at the .001 level. The magnitude of the estimators is reduced by 0.5% and 0.8% for the low incentive and high incentive groups when compared to the estimates obtained in the main regression. The parameter attenuation is negligible and does not significantly affect the interpretation of the results.

The additional model specifications displayed in Table 3.9 show despite some minor variances the magnitude of the estimated parameters across different identification strategies is stable. The parameter estimate across regression models for participants who responded affirmatively to the WTA question across different identification strategies ranges from 20.3% to 20.8% in the low incentive group and from 18.9% to 20% for those in the high incentive group. The statistical significance of the parameters is present in the parameter estimates for all models.

The magnitude of the parameter estimates is similar not only across models but also between the low incentive and the high incentive group. A t-test comparing the means for both experimental groups that received a payment reveals that the difference between the two is not statistically significant (Table 3.10). A possible explanation for this could be due to the difference between the monetary incentive amount ($25 or $50) and the amount expressed in the willingness to accept question ($10). The high incentive may not be sufficiently large in magnitude when compared to the low incentive to measurably affect quit rates. An alternative explanation lies in anchoring and adjustment: the explicit mention of the payment amount in the WTA question could be acting as an anchor for which the incentive payment represents a positive adjustment that biases the participant. If this case, it could be plausible that monetary incentive amounts higher than the anchored amount are sufficient to solidify the commitment mechanism.

The combined results from this paper are in line with Salize, Merkel, Reinhard, Twardella, Mann, and Brenner (2009), as we show that monetary incentives delivered to individuals are effective in increasing smoking cessation rates, as well as provide supporting evidence that, in addition to cost offsetting, payments can act as a commitment device (Russell, Volpp, Kwong, Cosgriff, Harhay, Zhu, and Halpern).

## 3.7 Conclusion

We explore whether the willingness to accept a monetary incentive to quit smoking can be used to target interventions for smoking cessation in pregnant women, and the effect monetary incentives have on quit rates in the presence of this preference to accept payments. Leveraging data from a clinic-based trial, we use individuals' responses to a question regarding their willingness to accept payment to stop smoking as administered in a baseline questionnaire and use urine cotinine test results from prenatal office visits to identify quit rates. Participants reported whether or not they had smoked in the past 30 days and provided a urine sample as part of the regular prenatal office visit. Participants were not informed about cotinine levels being measured in the urine sample. Every participant received a baseline incentive of $25, and participants in the experimental groups received an additional payment if they reported not having smoked in the past 30 days. The additional incentive payment for not smoking in the past 30 days was $25 for the low incentive group and $50 for the high incentive group. The mechanism used for the transfer was the use of CVS gift cards.

Participants in the treatment groups who answered positively to the question regarding their willingness to accept an incentive to stop smoking exhibited a higher average percentage of visits where their cotinine levels were below the threshold. Those par-

ticipants in the control group who answered the question positively as well did not exhibit the same results. A possible interpretation is that when individuals express an affirmative willingness to accept a monetary incentive to quit and subsequent payment is made, this transfer solidifies an underlying commitment mechanism that leads to increased quit rates. Individuals may feel a moral obligation to follow through on quitting because they expressed willingness to accept a stream of payments to stop smoking that they later received.

It is important to note the difference in incentive levels between the baseline questionnaire and the incentive provided to participants. The baseline questionnaire captured whether the participant was willing to accept a $10 incentive to quit smoking and the actual additional incentive the participants received was $25 for the low incentive group, and $50 for the high incentive group. Therefore, the observed results correspond to an incentive 2.5 times the amount the participant stated that she was willing to accept. This would indicate that while the effects observed start at an incentive of 2.5 times the WTA, the actual limit could actually be lower. Because WTA levels may vary by individual, the optimal incentive level offered to enable the mechanism should be further explored for more precise pricing. Additionally, it is plausible that the transfer itself acts as a solidifying mechanism that strengthens the commitment independent of its magnitude. Further research to isolate the effect of the transfer itself from the amount of the monetary incentive could provide more insight into policy implementation costs.

Another observation arises from the fact that both the low incentive and the high incentive group did not exhibit a statistically significant difference in quit rates despite the incentive levels being different. A probable explanation could be found

in the magnitude of the utility gains from smoking. Smokers derive a net gain in utility when they subtract their subjective costs from the subjective benefits derived from smoking. To them, quitting represents a net loss in utility. Consistent with the findings from Aumann, Treskova, Hagemann, and von der Schulenburg (2016), the preference against out-of-pocket costs would indicate that providing a monetary incentive could offset the loss in utility from quitting. The monetary incentive could then act as a mechanism to compensate for the utility lost when giving up smoking. In this scenario, smokers with a large net utility gain from smoking may be immune to lower incentive levels, which could explain the similarity in quit rates between both groups. If the $25 difference in the monetary incentive is not enough to observe higher quit rates in the high incentive group, it could be possible that only those smokers with a net utility gain at the margin are sensitive to the incentive. Further research exploring the pricing of the perceived costs and benefits of smoking, and the sensitivity to monetary incentives could enable a more precise policy design.

Lastly, these findings provide useful evidence that preferences regarding willingness to accept a monetary incentive to stop smoking followed by a cash incentive can be used as a leading indicator to target interventions and achieve increased quit rates.

Table 3.1: Sample statistics - Age by group

| Group | Obs | Mean Age | Std. Dev. | Min Age | Max Age |
|---|---|---|---|---|---|
| Control | 81 | 26.75 | 5.01 | 18.11 | 40.86 |
| Low incentive | 82 | 26.61 | 5.09 | 18.21 | 38.11 |
| High Incentive | 88 | 26.06 | 4.91 | 18.98 | 41.45 |
| All Groups | 251 | 26.46 | 4.99 | 18.11 | 41.45 |

Table 3.2: Sample statistics - Demographic characteristics - N (%)

| | Non-Hispanic/Latino | | Hispanic/Latino | | Not Reported | | Total | |
|---|---|---|---|---|---|---|---|---|
| White | 161 | (66%) | 2 | (40%) | 1 | (50%) | 164 | (65%) |
| African American | 71 | (29%) | 1 | (20%) | 1 | (50%) | 73 | (29%) |
| Multi-racial | 8 | (3%) | 2 | (40%) | 0 | (0%) | 10 | (4%) |
| Other/not reported | 4 | (2%) | 0 | (0%) | 0 | (0%) | 4 | (2%) |
| Total | 244 | (100%) | 5 | (100%) | 2 | (100%) | 251 | (100%) |

Table 3.3: Sample statistics - Marital status

| | Freq. | Percent | Cum. |
|---|---|---|---|
| Married | 51 | 20.40% | 20.40% |
| Married, separated | 5 | 2% | 22.40% |
| Divorced | 11 | 4.40% | 26.80% |
| Single | 178 | 71.20% | 98% |
| Domestic Partner | 5 | 2% | 100% |
| | 250 | 100.00% | |

Table 3.4: Sample statistics - Education and marital status

| | Marital Status | | | | | |
|---|---|---|---|---|---|---|
| Education | Married | Married, separated | Divorced | Single | Domestic Partner | Total |
| Less than high school | 10 | 2 | 2 | 42 | 2 | 58 |
| Graduated high school | 15 | 2 | 2 | 50 | 1 | 70 |
| GED degree | 3 | 0 | 2 | 21 | 0 | 26 |
| Some vocational or technical school | 1 | 1 | 0 | 4 | 0 | 6 |
| Vocational or technical school certificate | 3 | 0 | 0 | 3 | 0 | 6 |
| Some college | 15 | 0 | 5 | 42 | 0 | 62 |
| AA degree (2-year college degree) | 1 | 0 | 0 | 10 | 1 | 12 |
| BA or BS degree (4-year college degree) | 3 | 0 | 0 | 5 | 1 | 9 |
| Completed graduate school | 0 | 0 | 0 | 1 | 0 | 1 |
| Total | 51 | 5 | 11 | 178 | 5 | 250 |

Table 3.5: Sample statistics - Age Groups

| Age Group | Freq. | Percent | Cum. |
|---|---|---|---|
| 18-22 | 71 | 28.40% | 28.40% |
| 23-25 | 63 | 25.20% | 53.60% |
| 26-30 | 64 | 25.60% | 79.20% |
| 31-41 | 52 | 20.80% | 100% |
| Total | 250 | 100% | |

Table 3.6: Sample statistics - Income

| Income | Freq. | Percent | Cum. |
|---|---|---|---|
| Less than $20,000 | 156 | 62.15% | 62.15% |
| $20,001 to $35,000 | 55 | 21.91% | 84.06% |
| $35,001 to $50,000 | 21 | 8.37% | 92.43% |
| $50,001 to $65,000 | 11 | 4.38% | 96.81% |
| $65,001 to $80,000 | 5 | 1.99% | 98.80% |
| $80,001 to $120,000 | 1 | 0.40% | 99.20% |
| $120,000 or more | 2 | 0.80% | 100% |
| Total | 251 | 100% | |

Table 3.7: Sample statistics - Education

| Education | Freq. | Percent | Cum. |
|---|---|---|---|
| Less than high school | 58 | 23.20% | 23.20% |
| Graduated high school | 70 | 28% | 51.20% |
| GED degree | 26 | 10.40% | 61.60% |
| Some vocational or technical school | 6 | 2.40% | 64% |
| Vocational or technical school certificate | 6 | 2.40% | 66.40% |
| Some college | 62 | 24.80% | 91.20% |
| AA degree (2-year college degree) | 12 | 4.80% | 96% |
| BA or BS degree (4-year college degree) | 9 | 3.60% | 99.60% |
| Completed graduate school | 1 | 0.40% | 100% |
| Total | 250 | 100 | |

Table 3.8: Regression Results

| Office Visits Under Threshold (%) | Coef. | Std. Err. | t | Pr(> \|t\|) | [95% Conf. | Interval] | Significance |
|---|---|---|---|---|---|---|---|
| Control Group | | | | | | | |
| WTA = Yes | 0.0719 | 0.05 | 1.44 | 0.152 | -0.0265 | 0.1705 | |
| Treatment Group - Low Incentive | | | | | | | |
| WTA = No | 0.0497 | 0.0843 | 0.59 | 0.5560 | -0.1163 | 0.2158 | |
| WTA = Yes | **0.2077** | 0.0500 | 4.15 | **0.0000** | 0.1091 | 0.3063 | *** |
| Treatment Group - High Incentive | | | | | | | |
| WTA = No | 0.0579 | 0.0870 | 0.67 | 0.5060 | -0.1134 | 0.2293 | |
| WTA = Yes | **0.2003** | 0.0486 | 4.12 | **0.0000** | 0.1044 | 0.2962 | *** |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 3.9: Regression Results

| Office Visits Under Threshold (%) | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Group** | | | | |
| Control | | | | |
| WTA = Yes | 0.0987 | 0.0720 | 0.0720 | 0.0787 |
| | (0.0849) | (0.0500) | (0.0850) | (0.0840) |
| Treatment - Low | | | | |
| WTA = No | 0.0571 | 0.0497 | 0.0498 | 0.0606 |
| | (0.110) | (0.0843) | (0.111) | (0.110) |
| WTA = Yes | 0.207** | 0.208*** | 0.208** | 0.203** |
| | (0.0850) | (0.0501) | (0.0849) | (0.0838) |
| Treatment - High | | | | |
| WTA = No | 0.0332 | 0.0580 | 0.0580 | 0.0557 |
| | (0.108) | (0.0870) | (0.109) | (0.108) |
| WTA = Yes | 0.189** | 0.200*** | 0.200** | 0.192** |
| | (0.0846) | (0.0487) | (0.0845) | (0.0834) |
| **Controls** | | | | |
| Race | No | Yes | Yes | Yes |
| Income | No | Yes | Yes | Yes |
| Age | No | No | No | Yes |
| Constant | Yes | No | Yes | Yes |
| Observations | 261 | 251 | 251 | 251 |
| R-squared | 0.051 | 0.327 | 0.087 | 0.114 |

Standard errors in parentheses. Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 3.10: Two-sample t-test with equal variances (%)

| **Group** | Obs | Mean | Std. Err. | Std. Dev. | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| Treatment - Low WTA = Yes (0) | 71 | 0.2425218 | 0.0435902 | 0.3672974 | 0.1555839 | 0.3294597 |
| Treatment - High WTA = Yes (1) | 75 | 0.2248889 | 0.0337383 | 0.2921826 | 0.1576638 | 0.292114 |
| Combined | 146 | 0.2334638 | 0.0272952 | 0.3298096 | 0.1795159 | 0.2874117 |
| diff | | 0.0176329 | 0.0547806 | | -0.090645 | 0.1259108 |

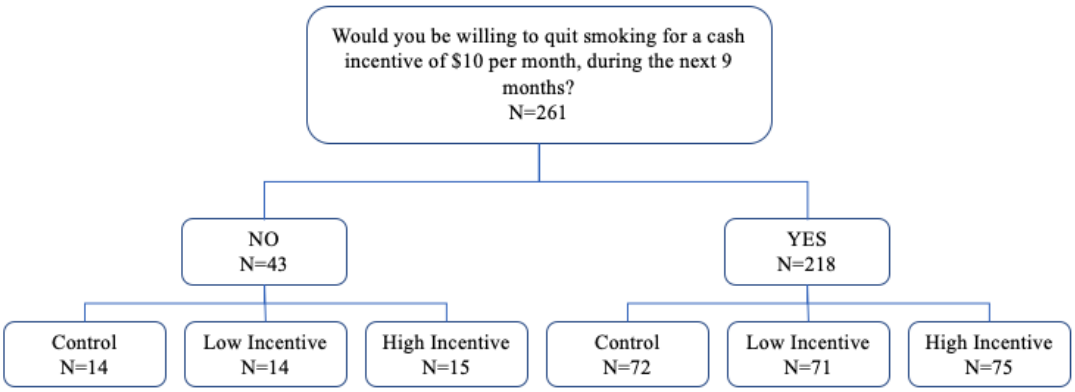
diff = mean(**0**) - mean(**1**) t = **0.3219**

Ho: diff = 0 degrees of freedom = **144**

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0

$Pr(|T| > |t|) =$ **0.6260** $Pr(|T| > |t|) =$ **0.7480** $Pr(|T| > |t|) =$ **0.3740**

Figure 3.1: Response distribution across groups



CHAPTER 4

# RELIABILITY OF SELF-REPORTED QUIT RATES IN SMOKING CESSATION INTERVENTIONS TARGETTING PREGNANT WOMEN

## 4.1 Introduction

The smoking population is at an increased risk of many adverse health outcomes, and when smoking occurs during pregnancy, the effects are compounded. Smoking during pregnancy increases the mother's risk of adverse cardiovascular events such as stroke (James et al. (2005)), acute myocardial infarction (James et al. (2006)), and venous thromboembolism (Heit et al. (2005)), as well as increased cervical (Yang et al. (1996)) and breast (Burton et al. (2000)) cancer, and an increased likelihood of presenting comorbidities (Roelands et al. (2009)).

This increased risk is a characteristic that, in pregnant women, extends to the unborn child. It appears as a three-fold increase in the likelihood of sudden infant death syndrome (T. M. Anderson et al. (2019), Centers for Disease Control and Prevention (2010))), brain and lung tissue damage in the fetus, lower birth weight, and premature delivery (Centers for Disease Control and Prevention (2010)).

A successful public health campaign requires correctly identifying the population at increased risk to balance the costs and benefits associated with their implementation to maximize campaign effectiveness. Correctly identifying smokers who are more likely to be successful in eliminating or reducing their smoking habit allows for the implementation of targeted interventions and a more efficient allocation of campaign

implementation costs because funds are focused on those individuals who are more likely to quit smoking.

Individuals who respond affirmatively to the question regarding their willingness to accept a monthly monetary incentive for smoking cessation during the prenatal period can achieve increased quit rates after receiving the payment as found in Chapter 3. The study was part of a clinic-based trial and found the increase in quit rates to be as high as 20% as measured by urine cotinine levels present in urine samples. Measuring campaign effectiveness using laboratory-based urine tests is impractical and costly because sample collection may be burdensome or unfeasible and laboratory-based tests present additional associated costs. Using self-reported smoking cessation rates from participants significantly reduces the complexity of data collection and eliminates challenges and costs associated with the construction of quit rate measures at scale. However, using self-reported data introduces significant disadvantages that can severely bias results.

Using self-reported data introduces bias at the originating point of the data (the individual's response) and through systematic errors. The first significant distortion in outcomes at the origination point is the response's dependency on participants' honesty regarding their nicotine consumption. Individuals may be more likely to provide socially acceptable answers or provide responses that are perceived as moral and ethical. Another bias may originate in the individuals' ability to accurately assess themselves because reporting tobacco in the past can be hard to remember. Lastly, individuals' ability to correctly interpret questions may hinder their ability to provide accurate answers. Systematic errors further present the possibility of introducing bias because the wording used to construct questions could cause confusion. Additionally,

rating scales or predetermined options can be imprecise or too restrictive. Sampling bias also exists because those respondents likely to provide information are those who may be part of a group that shares specific and unobserved characteristics.

This paper analyzes the effectiveness of using self-reported data to construct a quit rate measure and compares it to urine cotinine levels obtained from laboratory-based tests to measure the effectiveness of smoking cessation campaigns. Additionally, we seek to understand the viability of using such measures to guide and measure public health campaigns for smoking cessation during pregnancy that leverage willingness to accept monetary incentives as the intervention identification mechanism.

The remainder of this chapter is organized as follows: Section Literature Review reviews the relevant literature. In section Program Design, we describe the program design and implementation details. In section Methods, we describe the empirical methods used. In section Results, we discuss the results of our estimation. Lastly, in section Conclusion we provide concluding remarks.

## 4.2 Literature Review

Public health campaigns require implementing effective monitoring and evaluation controls to estimate what is happening in the population and measure the need for interventions as well as monitoring the effectiveness of ongoing campaigns. Performance management is considered one of the key components of implementing successful public health campaigns (Frieden (2014)).

Measuring the effectiveness of smoking cessation interventions in public health campaigns presents many challenges because it is often not feasible or practical to obtain

reliable quit rate data from participants. It can also be expensive to do so. The previous chapter analyzed quit rates using cotinine levels measured in urine samples provided by program participants. Cotinine is still considered the biomarker of choice for measuring tobacco exposure (Haufroid and Lison (1998)). However, urine sample collection can be burdensome and laboratory tests can be expensive. Alternate methods that do not rely on cotinine levels but are shown to be effective are those based on changes in the urinary 4-(methylnitrosamino)-1-(3-pyridyl)-1-butanol (NNAL) and urinary 7-methylguanine ($m^7$Gua) and 8-hydroxy-2'-deoxyguanosine (8-OHdG) levels (Kawasaki, Li, Ootsuyama, Nagata, Yamato, and Kawai (2020)), but these present the same collection and costs challenges as measuring cotinine levels due to the need for laboratory-based tests.

During each office visit, participants reported whether they had smoked in the past 30 days and were not made aware of urine cotinine level testing of the samples collected. These reports are a good candidate measure of quit rates because the implementation of data collection methods to gather quit rate data from self-reports has a significantly reduced cost. However, prior studies analyzing the validity and reliability of self-reported data on the consumption of another addictive good (alcohol) found that self-reports are affected by bias(Embree and Whitehead (1993)). An interesting finding from the study was that the wording of the question itself played a significant role because of the ability to facilitate recall and affect willingness to provide a socially desirable response.

An empirical analysis of self-assessed measures of health finds consistency from both an objective and subjective point of view (Vaillant and Wolff (2012)), providing a

promising foundation for this analysis as it supports the intuition that self-reports can monitor campaign effectiveness.

The ability to simultaneously observe quit rates based on urine cotinine test results and the corresponding self-reported values allows for the analysis of the deviations between the two rates. A retrospective analysis studying the relationship between cotinine testing and self-reported quit rates before a medical procedure intervention noted that approximately 15% of participants falsely report abstinence (Hart, Rainer, Taunton, Mabry, Berry, and Abdel (2019)). Our study is similar in that it attempts to understand the relationship between self-reported quit rates and urine cotinine levels.

## 4.3 Program Design

Similar to Chapter 3, this study analyzes data obtained from a study performed by the Indiana University and approved by its institutional review board (Middlestadt et al. (2020)). Participants recruited from 11 prenatal clinics located in Indiana were initially screened using a questionnaire to determine eligibility. Of particular importance to this analysis, the questionnaire recorded demographic characteristics. After determining eligibility, eligible women were identified and enrolled in the program and referred to research staff to administer an intake form and a baseline survey. The baseline survey captured the individual's willingness to accept a cash incentive to quit smoking. A questionnaire was given during each prenatal care office visit, recording the date of the office visit, urine cotinine test results, and self-reported consumption of nicotine in the 30 days leading to the visit, among other data points.

The program was composed of a control group and two experimental groups ("low incentive" and "high incentive"). The control group offered a $20 CVS gift card as a baseline incentive for each attended office visit. The low incentive group offered the baseline incentive plus an additional $25 if the individual reported not having smoked in the prior 30-day period. The high incentive group offered the baseline incentive plus $50 if the individual reported not having smoked cigarettes in the past 30 days. Unknown to the participants, urine samples were collected during each visit and sent to a laboratory to test for cotinine levels. The additional incentives for the intervention groups were not conditional on the urine cotinine test results.

Postpartum data from medical records and recorded responses to a postpartum questionnaire are available for each participant. Please refer to Chapter 3 for additional details regarding the program design.

## 4.4 Data

The data used for this analysis corresponds to the data set obtained as part of the clinic-based smoking cessation program implemented by Indiana University as noted in Chapter 3. A summary of the previous chapter follows. Below is a summary of the previous chapter. The study focused on smoking cessation during pregnancy and provided different levels of cash incentives in two treatment arms. After being deemed eligible for program participation and enrollment, participants completed a series of questionnaires administered at various stages of the program. There are two questionnaires of particular interest to this analysis: the baseline questionnaire administered at the beginning of the program and the monthly visit questionnaire capturing data obtained during each prenatal care office visit. The baseline questionnaire captures individuals' willingness to accept a stream of payments in exchange

for smoking cessation. This questionnaire is administered once at the beginning of the program. The visit questionnaire captures responses to the question asking if the participant smoked in the 30 days leading to the visit and tests results for urine cotinine levels.

The study enrolled 333 pregnant women for further assignment to a control group and two intervention groups. The control group was composed of 113, and the treatment arms were composed of 109 in the low incentive group and 111 in the high incentive group. Approximately 97% of the participants identified themselves as non-Hispanic (97%). The largest race group was white women (66%) followed by Black/African American women (29%). Please refer to Table 3.2 for additional race statistics. A detailed description of the demographic characteristics for the study can be found in Chapter 3 because this study makes use of the same data. Additional data aggregations can be found in Chapter 3 as well. These categorize participants according to their marital status (Table 3.3), age group (Table 3.5), income (Table 3.6), and education level (Table 3.7). Please refer to Figure 3.1 for the distribution of participants according to their willingness to accept a monetary incentive to stop smoking.

The data used to construct the quit rate measure based on self-reports leverages a question in the questionnaire administered during each office visit. The specific wording was *"Has the participant smoked cigarettes in the past 30 days?"* with two possible options (yes or no). Positive responses were coded with the number one, while negative responses were coded with the number zero. The number of responses for the participants at each office visit displayed according to their urine cotinine levels in Table 4.1. We can also observe that falsely reported quit rates are consistent at an average of 23% across visits. Real quit responses gradually increase and peak

at the fifth visit and then again at the eighth visit, with an average accuracy of 13%. Details are available in Table 4.2.

## 4.5 Methods

Consistent with the methods employed in the analysis in the previous chapter, we calculate a variable to estimate the relationship between quit rates and the participants' willingness to accept monetary incentives for smoking cessation. The calculation of quit rates uses individuals' responses to a question administered during each office visit inquiring about their consumption of cigarettes in the 30 days before the visit. The specific wording of the question was *"Has the participant smoked cigarettes in the past 30 days?"*. Participants were required to provide an answer by selecting one of two options available for selection (yes or no). A dummy variable was available for each visit the participant attended, and the data recorded used a value of one and zero, respectively, to denote yes and no. Once we constructed our quit rate measure, we created a new variable that captures the percentage of office visits where participants reported not having smoked.

In alignment with our prior estimation method and identification strategy, we created an interaction term between responses to the question in the baseline questionnaire that captures the individual's willingness to quit smoking in return for a cash incentive and a categorical variable identifying the experimental group. We estimate the relationship between willingness to accept and our newly constructed quit rates based on self-reports applying a linear regression model of the form:

$$SRPCTVUT_{it} = \beta_0 + \beta_1(Group_{it} \text{ x } WTA_{it}) + \beta_2 Demo_{it} + \epsilon_{it}$$

where $SRPCTVUT_{it}$ is the percent of office visits that the participant attended and reported not having smoked in the 30 days prior to the visit, $Group_{it}$ is the treatment arm (coded as 0 for the control group, 1 for the low incentive group, and 2 for the high incentive group), $WTA_{it}$ is an indicator for willingness to accept that takes the value of 1 if the individual is willing to accept a payment to stop smoking, $Demo_{it}$ is a vector of demographic controls inclusive of race, ethnicity, income, and age, and $\epsilon_{it}$ is the error term.

Robustness checks comparing self-reported quit rates to laboratory-based urine cotinine test results use data captured during each office visit and were included in the monthly questionnaire as outlined in the previous chapter.

Lastly, we compare our estimates to those obtained using our original linear model and the laboratory-based test results for urine cotinine levels as outlined in Chapter 3. We first run a multivariate analysis of variance for both linear models and obtain test statistics for our joint estimation. We then test for joint significance of the predictors across models to derive further conclusions.

## 4.6 Results

Table 4.3 shows results from the main model specification. Participants with an affirmative response to the question regarding their willingness to accept showed increased self-reported quit rates with averages between 32.2% and 33.2% regardless of whether they were in the control or any of the treatment groups. This average increase is statistically significant at the 0.01 level for all three groups that share the same willingness to accept preferences. Unlike our previous results, the average increase of self-reported quit rates is statistically significant also for the control group,

which was not a feature observed in lab-based quit rates. We do not observe an increase in self-reported quit rates for any groups among the individuals not willing to accept incentives, which is a characteristic shared with the prior model.

Following the procedure and reasoning in the previous chapter, we estimate a simplified regression model without control variables. We observe that participants who share a willingness to accept monetary incentives in both treatment arms exhibit an increase in quit rates of 33.4%, 32.6%, and 27.2% for the control, low, and high incentive groups (Table 4.4, regression 1). The observed increases are statistically significant at the 0.001 level for the control and low incentive groups and the 0.05 level for the high incentive group. The magnitude change is negligible and does not affect the interpretation given the context of quit rates during prenatal visits.

Regression 3 in Table 4.4 shows that adding a constant term to the main model specification reduces the quit rate increases by approximately 4% on average. The standard errors almost double in magnitude, reducing statistical significance to the 0.05 level. Adding a control variable for the participants' age to the model yields parameter estimates of 29.6%, 28.4%, and 27.6% for the control, low incentive, and high incentive groups (Table 4.4, regression 4). The newly obtained estimates are significant at the .05 level.

Similar to our previous findings, the additional model specifications in Table 4.4 show that the identification strategy is mostly stable, exhibiting minor variances in the magnitude of the estimated parameters. Self-reported measures of quit rates produce parameter estimates across regression models for participants who responded

affirmatively to the WTA question across different identification strategies ranging from 27.6% to 33.4% on average across groups.

A t-test comparing the means for both treatment groups shows that the difference between the two is not statistically significant (Table 4.5). The interpretation from our prior findings regarding the difference between the monetary incentive levels and the amount specified in the WTA question is not sufficiently large. Additionally, the anchoring and adjustment alternative explanation is also applicable: the question anchors the participant on a given value, and a subsequent delivered monetary incentive of comparable magnitude is enough to solidify the commitment device.

These results suggest an overestimation of self-reported quit rates of 13% (on average), results that support prior findings identifying false reporting of abstinence by 15% (Hart et al. (2019)). It is not surprising to observe an overestimation of self-reported quit rates compared to the lab-based quit rates. Individuals may be incorrectly recalling their past behavior regarding smoking, misrepresenting small quantities of cigarettes smoked as having quit, or simply lying to obtain the incentive. Table 4.6 shows regression results for our multivariate multiple regression analysis displaying regression coefficients side by side. We can observe an overestimation of self-reported quit rates for the treatment groups by a consistent 13% for the participants willing to accept payments for smoking cessation. The t-tests comparing treatment groups for both the self-reported and the lab-based quit rate measures show that the difference between the groups is not statistically significant. This leads to the interpretation that monetary incentives increase actual quit rates by 20% for individuals who exhibit a willingness to accept payments for smoking cessation. Furthermore, this suggests

that actual quit rates are 11% lower than what individuals report regarding their quit rates.

We perform a multivariate analysis of variance to determine if our joint models are statistically significant (Table 4.7). The overall model is statistically significant as is a multivariate test for the predictor of interest. We perform a joint hypothesis test that the coefficients associated with the interaction coefficient term are equal to zero in Table 4.8. Results show that we can reject the null hypothesis that the coefficients across the two equations are simultaneously equal to zero. Lastly, in Table 4.9 we test the null hypothesis that the coefficient of the interaction terms is the same on both regressions. We conclude that the regression coefficient using a laboratory-based quit rate measure as a dependent variable equals the regression coefficient using the self-reported quit rate measure as a dependent variable. We can observe that the hypothesis tests for the treatment groups where the participants responded affirmatively to the WTA question show that the differences in the two sets of coefficients are statistically significant.

## 4.7 Conclusion

In the previous chapter, we explored the use of pregnant women's willingness to accept a monetary incentive to quit smoking as an identification mechanism to target smoking cessation interventions that use monetary incentives.

We conclude that WTA is an effective mechanism to identify individuals who exhibit potentially higher quit rates, as measured using laboratory-based tests for urine cotinine levels. However, obtaining samples for laboratory testing in large-scale public health campaigns is both unfeasible and potentially costly. We explore using self-

reports to measure quit rates because of the cost-effectiveness of the data collection process in large-scale campaigns. While self-reports are traditionally an unreliable source of measurement, the study design allowed us to observe both actual and self-reported values. The data set records the laboratory-based test results for urine cotinine levels and the self-reported response recorded during the prenatal visits. This feature allows us to interpret self-reported outcomes relative to actual quit rates measured from urine cotinine levels through the individuals' responses to monitor campaign effectiveness.

Unsurprisingly, self-reports are 13% higher (on average) compared to actual quit rates. These results are consistent with prior studies analyzing the difference between cotinine testing and self-reported quit rates. The discrepancy between the self-reported data and the lab-based results could originate from multiple sources because bias can originate at the individuals' responses and through systematic errors.

The presence of distortion in responses also depends on the participants' honesty regarding their smoking habits. In the case of pregnant women, pressure from social and perceived norms could drive respondents to provide socially acceptable answers or responses that are perceived as moral and ethical.

Another bias could originate from individuals' inability to recall smoking habits or to assess themselves. At low levels of cigarette smoking, individuals may also feel tempted to report having quit as they may consider that they practically achieved the goal when, in fact, they haven't. Lastly, the ability to correctly interpret the question in the survey or the underlying assumptions and definitions may lead to inaccurate answers. Systematic errors present further obstacles and potential sources of bias

through wording used to construct questions, the rating scales used, or predetermined answer options.

These findings confirm our prior results showing that willingness to accept a monetary incentive to stop smoking followed by a cash incentive can be used as a leading indicator to target interventions and achieve increased quit rates. Furthermore, our analysis provides a reference point to monitor campaign performance using a quit rate measure constructed from self-reports that closely follow actual urine cotinine levels from laboratory-based tests. The findings from this study suggest that campaign officials should consider implementing data collection mechanisms to capture self-reported quit rates because they provide a reliable indication of campaign effectiveness.

Table 4.1: Self-reported quit rates and urine cotinine levels

| Self-reported Smoking | UC Below Threshold | UC Above Threshold | UC Below Threshold (%) | UC Above Threshold (%) |
|---|---|---|---|---|
| **1st Visit** | | | | |
| No | 30 | 61 | 9.4% | 19.2% |
| Yes | 9 | 218 | 2.8% | 68.6% |
| Total | 39 | 279 | 12.3% | 87.7% |
| **2nd Visit** | | | | |
| No | 36 | 69 | 12.6% | 24.1% |
| Yes | 7 | 174 | 2.4% | 60.8% |
| Total | 43 | 243 | 15.0% | 85.0% |
| **3rd Visit** | | | | |
| No | 37 | 65 | 13.7% | 24.1% |
| Yes | 4 | 164 | 1.5% | 60.7% |
| Total | 41 | 229 | 15.2% | 84.8% |
| **4th Visit** | | | | |
| No | 42 | 52 | 17.9% | 22.1% |
| Yes | 4 | 137 | 1.7% | 58.3% |
| Total | 46 | 189 | 19.6% | 80.4% |
| **5th Visit** | | | | |
| No | 35 | 43 | 18.4% | 22.6% |
| Yes | 3 | 109 | 1.6% | 57.4% |
| Total | 38 | 152 | 20.0% | 80.0% |
| **6th Visit** | | | | |
| No | 20 | 39 | 14.1% | 27.5% |
| Yes | 3 | 80 | 2.1% | 56.3% |
| Total | 23 | 119 | 16.2% | 83.8% |
| **7th Visit** | | | | |
| No | 7 | 24 | 8.6% | 29.6% |
| Yes | 3 | 47 | 3.7% | 58.0% |
| Total | 10 | 71 | 12.3% | 87.7% |
| **8th Visit** | | | | |
| No | 6 | 7 | 17.1% | 20.0% |
| Yes | 1 | 21 | 2.9% | 60.0% |
| Total | 7 | 28 | 20.0% | 80.0% |
| **9th Visit** | | | | |
| No | 0 | 1 | 0.0% | 14.3% |
| Yes | 0 | 6 | 0.0% | 85.7% |
| Total | 0 | 7 | 0.0% | 100.0% |
| **Total** | **247** | **1317** | **15.8%** | **84.2%** |

Responses where participants reported not having smoked in the 30-day period leading to the office visit, and urine cotinine levels below the acceptable limit

Table 4.2: True and false quit reports

| **Visit** | **True Quit Report** | **False Quit Reports** |
|---|---|---|
| 1st Visit | 9.4% | 19.2% |
| 2nd Visit | 12.6% | 24.1% |
| 3rd Visit | 13.7% | 24.1% |
| 4th Visit | 17.9% | 22.1% |
| 5th Visit | 18.4% | 22.6% |
| 6th Visit | 14.1% | 27.5% |
| 7th Visit | 8.6% | 29.6% |
| 8th Visit | 17.1% | 20.0% |
| 9th Visit | 0.0% | 14.3% |
| **Total** | 13.6% | 23.1% |

Table 4.3: Regression results

| Office Visits Reported Quitting (%) | Coef. | Std. Err. | t | Pr(> \|t\|) | [95% Conf. Interval] | | Significance |
|---|---|---|---|---|---|---|---|
| Control Group | | | | | | | |
| WTA = Yes | **0.3216** | 0.0696 | 4.62 | **0.000** | 0.1843 | 0.4588 | *** |
| Treatment Group - Low Incentive | | | | | | | |
| WTA = No | 0.0347 | 0.0843 | 0.30 | 0.768 | -0.1965 | 0.2660 | |
| WTA = Yes | **0.3317** | 0.0696 | 4.76 | **0.000** | 0.1944 | 0.4689 | *** |
| Treatment Group - High Incentive | | | | | | | |
| WTA = No | 0.0895 | 0.1212 | 0.74 | 0.461 | -0.1492 | 0.3281 | |
| WTA = Yes | **0.3314** | 0.0678 | 4.89 | **0.000** | 0.1979 | 0.4649 | *** |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 4.4: Regression results

| Office Visits Under Threshold (%) | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Group** | | | | |
| Control | | | | |
| WTA = Yes | 0.334*** | 0.322*** | 0.283** | 0.296** |
| | (0.119) | (0.0697) | (0.118) | (0.115) |
| Treatment - Low | | | | |
| WTA = No | -0.00442 | 0.0347 | -0.00604 | 0.0155 |
| | (0.155) | (0.117) | (0.155) | (0.150) |
| WTA = Yes | 0.326*** | 0.332*** | 0.293** | 0.284** |
| | (0.120) | (0.0697) | (0.118) | (0.115) |
| Treatment - High | | | | |
| WTA = No | 0.00384 | 0.0895 | 0.0520 | 0.0474 |
| | (0.152) | (0.121) | (0.152) | (0.148) |
| WTA = Yes | 0.272** | 0.331*** | 0.292** | 0.276** |
| | (0.119) | (0.0678) | (0.118) | (0.114) |
| **Controls** | | | | |
| Race | No | Yes | Yes | Yes |
| Income | No | Yes | Yes | Yes |
| Age | No | No | No | Yes |
| Constant | Yes | No | Yes | Yes |
| Observations | 261 | 251 | 251 | 251 |
| R-squared | 0.078 | 0.506 | 0.126 | 0.180 |

Standard errors in parentheses. Signif. codes *** p<0.01, ** p<0.05, * p<0.1

Table 4.5: Two-sample t-test with equal variances (%)

| Group | Obs | Mean | Std. Err. | Std. Dev. | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| **Treatment - Low** | | | | | | |
| WTA = Yes (0) | 71 | 0.4419517 | 0.0510816 | 0.4304213 | 0.3400727 | 0.5438308 |
| **Treatment - High** | | | | | | |
| WTA = Yes (1) | 75 | 0.3879683 | 0.0476058 | 0.4122784 | 0.2931116 | 0.4828249 |
| Combined | 146 | 0.4142205 | 0.0348102 | 0.4206129 | 0.3454196 | 0.4830214 |
| diff | | 0.0539835 | 0.069743 | | -.0838687 | 0.1918356 |

diff = mean(**0**) - mean(**1**) t = **0.7740**

Ho: diff = 0 degrees of freedom = **144**

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0

$Pr(|T| > |t|) =$ **0.7799** $Pr(|T| > |t|) =$ **0.4402** $Pr(|T| > |t|) =$ **0.2201**

Table 4.6: Multivariate multiple regression results

| Equation | Obs | Parms | RMSE | "R-sq" | F | P |
|---|---|---|---|---|---|---|
| Lab-based | 251 | 8 | .2869171 | 0.3268 | 14.74328 | 0.0000 |
| Self-reported | 251 | 8 | .399513 | 0.5057 | 31.07676 | 0.0000 |

| Quit Rates | (1) Lab-based | (2) Self-Reported |
|---|---|---|
| **Control Group** | | |
| WTA = Yes | 0.0720 | 0.322*** |
| | (0.0500) | (0.0697) |
| **Treatment - Low Incentive Group** | | |
| WTA = No | 0.0497 | 0.0347 |
| | (0.0843) | (0.117) |
| WTA = Yes | 0.208*** | 0.332*** |
| | (0.0501) | (0.0697) |
| **Treatment - High Incentive Group** | | |
| WTA = No | 0.0580 | 0.0895 |
| | (0.0870) | (0.121) |
| WTA = Yes | 0.200*** | 0.331*** |
| | (0.0487) | (0.0678) |
| Observations | 251 | 251 |
| R-squared | 0.327 | 0.506 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.7: Multivariate analysis-of-variance (MANOVA)

| Source | Statistic | | df | F(df1, | df2) | =F | Prob>F | |
|---|---|---|---|---|---|---|---|---|
| Model | W | 0.4558 | 10 | 20 | 480 | 11.55 | 0.0000 | e |
| | P | 0.5784 | | 20 | 482 | 9.81 | 0.0000 | a |
| | L | 1.1187 | | 20 | 478 | 13.37 | 0.0000 | a |
| | R | 1.047 | | 10 | 241 | 25.23 | 0.0000 | u |
| Residual | | | 241 | | | | | |
| Study Group # WTA | W | 0.7329 | 5 | 10 | 480 | 8.07 | 0.0000 | e |
| | P | 0.2788 | | 10 | 482 | 7.81 | 0.0000 | a |
| | L | 0.3485 | | 10 | 478 | 8.33 | 0.0000 | a |
| | R | 0.2941 | | 5 | 241 | 14.18 | 0.0000 | u |
| Race | W | 0.9351 | 2 | 4 | 480 | 4.09 | 0.0028 | e |
| | P | 0.0654 | | 4 | 482 | 4.07 | 0.0029 | a |
| | L | 0.0689 | | 4 | 478 | 4.11 | 0.0027 | a |
| | R | 0.06 | | 2 | 241 | 7.23 | 0.0009 | u |
| Income | W | 0.987 | 3 | 6 | 480 | 0.52 | 0.7896 | e |
| | P | 0.013 | | 6 | 482 | 0.53 | 0.7888 | a |
| | L | 0.0132 | | 6 | 478 | 0.52 | 0.7903 | a |
| | R | 0.012 | | 3 | 241 | 0.97 | 0.4094 | u |
| Residual | | | 241 | | | | | |
| Total | | | 251 | | | | | |

e = exact, a = approximate, u = upper bound on F

Table 4.8: Linear hypothesis test

| | | | |
|---|---|---|---|
| (1) | [Lab-based]Control Group # WTA(Yes) | = | 0 |
| (2) | [Self-reported]Control Group # WTA(Yes) | = | 0 |
| (3) | [Lab-based]Treatment-Low # WTA(No) | = | 0 |
| (4) | [Self-reported]Treatment-Low # WTA(No) | = | 0 |
| (5) | [Lab-based]Treatment-Low # WTA(Yes) | = | 0 |
| (6) | [Self-reported]Treatment-Low # WTA(Yes) | = | 0 |
| (7) | [Lab-based]Treatment-High # WTA(No) | = | 0 |
| (8) | [Self-reported]Treatment-High # WTA(No) | = | 0 |
| (9) | [Lab-based]Treatment-High # WTA(Yes) | = | 0 |
| (10) | [Self-reported]Treatment-High # WTA(Yes) | = | 0 |

$F(10,243) = 5.35$
$Prob > F = 0$

Table 4.9: Hypothesis tests

**Control Group**

| | | |
|---|---|---|
| Test | = | [Lab-based]Control Group # WTA(Yes) - [Self-reported]Control Group # WTA(Yes) = 0 |
| F(1, 243) | = | 19.67 |
| Prob > F | = | 0.0000 |

**Treatment Group - Low Incentive**

| | | |
|---|---|---|
| Test | = | [Lab-based]Treatment-Low # WTA(No) - [Self-reported]Treatment-Low # WTA(No) = 0 |
| F(1, 243) | = | 0.02 |
| Prob > F | = | 0.8745 |

| | | |
|---|---|---|
| Test | = | [Lab-based]Treatment-Low # WTA(Yes) - [Self-reported]Treatment-Low # WTA(Yes) = 0 |
| F(1, 243) | = | 4.85 |
| Prob > F | = | 0.0286 |

**Treatment Group - High Incentive**

| | | |
|---|---|---|
| Test | = | [Lab-based]Treatment-High # WTA(No) - [Self-reported]Treatment-High # WTA(No) = 0 |
| F(1, 243) | = | 0.10 |
| Prob > F | = | 0.7477 |

| | | |
|---|---|---|
| Test | = | [Lab-based]Treatment-High # WTA(Yes) - [Self-reported]Treatment-High # WTA(Yes) = 0 |
| F(1, 243) | = | 5.73 |
| Prob > F | = | 0.0174 |

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