The Impact of Diabetes Education on Behavior and Health – A Propensity Coarsened Exact Matching Application

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Abstract

Using the Behavioral Risk Factor Surveillance System (BRFSS) survey from 2013 to 2018, this study investigates diabetes education's effects among diabetes respondents on different health outcomes and risky behaviors. Using Propensity Coarsened ExactMatching (CEM) for diabetes education, this study found that receiving diabetes education positively affects one's self-reported health outcomes and negatively affects one's propensity to engage in risky behaviors. Specifically, this study shows evidence that receiving diabetes education reduces the number of days that the survey participants do not feel well, physically. It also reduces respondent's alcohol intake and the probability of respondents being a current smoker. Moreover, this study also shows that having diabetes education increases the frequency of having an A1C check-up and increases physical activity among respondents. This study also is the first to use repeated cross-sectional data across all states in the U.S. to investigate the long-term effect of diabetes educations on mental and physical health. This study reaffirms the findings of prior studies on diabetes education's impact on other health outcomes such as exercise and other risky behaviors such as smoking and drinking.

Keywords: diabetes, propensity, behavioral risk factor surveillance system, health outcomes

1. Introduction

Diabetes is a common and expensive disease associated with severe and premature mortality. According to the National Diabetes Statistics Report for 2020, the number of people living with the disease is over 34,2 million. This number is a substantial 10.5% of the United States of America population and a significant increase from the 18.2 million people reported to have suffered from diabetes in 2012. Further, without adequate interference from governmental policies, this number is expected to increase. The impact of diabetes is so severe that in 2017 it cost the U.S. an estimated 327 billion dollars, which translates to an average cost per person in the U.S. of roughly 10,000 dollars per year.

Moreover, diabetes is the sixth leading cause of death after heart disease, cancer, injuries, respiratory diseases, and stroke. Diabetes mortality and the financial cost of diabetes are expected to rise without proper interventions from governmental policies. Many diabetes education programs have attempted to mitigate the adverse effects of diabetes on one's health. However, the levels of effectiveness for these programs are very different across study designs and samples. Generally, the definition of diabetes education programs can be broad, and thus the implementation of these programs based on those definitions can be very different. As such, there has not been a universal approach to implementing diabetes education for patients, making it more difficult for policymakers to understand the most effective course of action.

Nevertheless, diabetes education programs have proved to have significant economic implications. Several studies have shown that effective diabetes self-management significantly reduces both complications and health care costs (Caspersen 2011; Stetson 2011), although the estimated savings per diabetes education program can vary considerably. For instance, Balamurugan et al. 2006 showed that the cost-saving was estimated at 415 dollars per program completer over three years, while Chase et al. 2003 found it to be 163 dollars over six months. Similarly, Cranor et al. 2003 show that education reduced the total average direct medical cost by 1,200 dollars, from 3,071 dollars to 1,872 dollars per patient per year, while De Weerdt et al. 1991 found the total cost to be 2,324 dollars per patient per year. In another context, having diabetes education is found to have an incremental cost-effectiveness ratio of 55,726 dollars per quality-adjusted life-year (Brownson et al., 2009), 12,994 dollars for trial data per quality-adjusted life-year, and 5,047 dollars per quality-adjusted life-year for real-world data (Gillett et al., 2010). Although diabetes education programs' economic cost-saving structure is widely different across different studies, they are generally quite useful. However, not many diabetes patients are informed of these diabetes education programs, which is merely because health care professionals are not aware of the positive impacts of such programs. Little is still known about the effectiveness of diabetes treatment and the prevention of behavior and lifestyles.

Using observational survey data from the Behavioral Risk Factor Surveillance System (BRFSS) survey, this study employs the Propensity Coarsened Exact Matching (CEM) method to measure diabetes education's effects on various health factors. This study uses a simple theoretical framework to investigate the impacts of having diabetes education on health outcomes through two different models. The first model examines the direct relationship of diabetes education on behaviors and risky behaviors, including the frequency of A1C doctor check-ups, the likelihood of exercising, drinking frequency, and the likelihood of being a current smoker. The second model investigates the direct relationship between diabetes education and general health outcomes, including bad mental and physical health days.

With numerous controlling factors in the study, which includes demographics, health insurance, chronic health conditions, and different fixed effects, this study provides evidence that having diabetes education increases the likelihood of exercising by 6.7% on average and reduces the probability of being a smoker by 4.8% on average. Based on the count model or those who have experienced bad physical health days, the expected change in log of bad physical health days for having diabetes education is -0.97, holding other variables constant. Based on the zero-inflated model, having diabetes education reduces the odds of having bad physical health days by 0.90 times among those who never experienced bad physical health days. Similarly, for other zero-inflated count models, the study also shows that the expected change in log of alcohol consumption for having diabetes education is -0.82, holding all else constant. Moreover, having diabetes education decreases the odds of having drinks by 0.89 times among those who did not report having a drink in the past 30 days. Lastly, the expected change in log of A1C check-up for having diabetes education is 1.13 among those who have had A1C check-ups in the past 30 days, holding all else constant. Moreover, having diabetes education increases the odds of having A1C doctor check-ups by 2.5 times among those who never had A1C check-ups in the past 30 days.

The results have a significant implication. This study aims to increase the knowledge and skills of people with diabetes to help them successfully self-manage the disease. Previous research indicates that 50% to 80% of individuals with diabetes have significant deficits in knowledge about the management of their condition (Clement et al.). As a result, diabetes patients underestimate the disease's detrimental effect and thus fail to manage it. Even in primary care settings, little time is still devoted to diabetes management during routine doctor visits (Barnes CS, Ziemer DC, Miller CD, et al.), which may occur because doctors and health-care professionals do not fully understand the significant implications that diabetes can cause in the long run.

On the one hand, public health sectors failed to express the significance of diabetes disease. On the other hand, they were unable to prioritize the importance of diabetes education for diabetes patients. This paper aims to inform the general public about the positive impacts of diabetes education programs on behaviors and lifestyles, thus motivating policymakers to focus on widely acceptable interventions with a stable cost.

This paper is not the first research to investigate the effect of diabetes education programs. Previous research has repeatedly shown the evaluated effect of diabetes self-management on various health factors, such as physical activity and impulsive behaviors. However, this study differs from previous studies in two significant ways. First, rather than using short sample periods at mainly local and state levels, this study is the first to investigate the long-term impact of diabetes education at the national level. With well over 2.7 million observations spanning from 2013 to 2018 and well-designed econometric models, the estimates yielded from this study are confidently efficient and consistent. Second, this paper is the first to attempt at finding the causal effects of diabetes education programs. With the dense controls and the utilization of the Propensity Coarsened Exact Matching (CEM) method, this study aims to find unbiased estimates of diabetes education.

This paper is organized as follows. Section 2 outlines the mechanisms and previous literature review on diabetes education programs. This section also discusses the economics of diabetes education. Section 3 presents the data and empirical approach, including a propensity score analysis on the dataset and its descriptive literature. Section 4 illustrates the methodologies used on the dataset and presents the results. In Section 5, this paper shows the goodness of fits of the estimates, in which it shows that the estimates produced are consistent and accurate. Section 6 concludes the article.

2. Methodology and Results

Model 1

This sub-section analyzes diabetes education's effects on behavioral outcomes, including Alcohol Consumption, A1C Checkups, Exercise, and Smoking. It employs logistic regressions for binary outcomes, and zero-inflated negative binomial for count outcomes. All the regressions are weighted using the propensity or distance weights from the matching sample. These weights take different values in which 1 represents a perfect matched observation, and 0 illustrates a non-matched observation. The technical practice for the matching method utilized in this study follows previous research closely (Ho, Imai, King, Stuart 2011).

For Binary Outcomes, this paper faces quite a difficult task given the large imbalance in classification for some of the primary dependent variables, such as smoking and exercising. After re-coding the data, class 0, or respondents who are non-smokers, consists of significantly fewer observations than class 1, or respondents who are smokers. The same situation applies to respondents who were physically active or exercised during the past 30 days, although the magnitude of the imbalance classification is much less. In such cases, when the binary response variable is imbalanced in the data so that the proportion of class 1 heavily dominates the class 0 proportion, then the logistic model cannot perform well to detect the outcome with low proportion. In other words, the model's reporting specificity would be very low, which means the probability of detecting class 1 cases would be unsatisfying low. Thus, they result in biased predictions and misleading accuracies. There are many methods to tackle imbalanced classification problems, but those are not easy to perform in such a large dataset. This paper imposes two strategies to combat this issue and compare the results to assess the models' robustness. The first method is a mix of under-sampling and over-sampling, where under-sampling class 1 and over-sampling class 0 are performed to produce a perfect proportion of 50/50 for class 1 and class 0. The first model's problem is that the data generated from oversampling has an expected amount of repeated observations. The data generated from under-sampling is deprived of important information from the original data. This issue leads to some inaccuracies in the resulting performance. The second method is to simply impose under-sampling for class 1, in which a sample of class 1 would be cut randomly to get to the same amount of observations as class 0. This method would result in a loss of vital information from class 1, although it keeps all the information in class 0.

However, by imposing the two methods and properly comparing the two results, this paper should yield estimates in the middle range of biases, producing arguably the best and most accurate estimates. These techniques are commonly used in previous literature in imbalanced classification logistic models, as they would significantly improve prediction accuracy. This section will present the first sampling method results [3].

For Continuous Outcomes, this paper also faces an issue, in which there is comparably a large number of respondents who report having 0 drinks in the past 30 days. This problem is not as significant for respondents who report having their A1C check over the past year before the interview date. This paper, running various model fit tests, found that neither the Poisson model nor the Negative Binomial model is appropriate for the physical and mental health model due to over-dispersion, which reported well over 1. Therefore, this paper employs zero-inflated count models for these dependent variables of interest[4].

Table 1: Regression Results for Risky and Health Outcomes

Dependent variable: Risky and Health Outcomes

	Current Smokers	Exercise	Alcohol Consumption	A1C Checkups
	Logistics	*Logistics*	*Zero-inflated NB*	*Zero-inflated NB*
	(1)	(2)	(3)	(4)
diabetes_education	0.221	0.295	0.195	0.130
	(0.046)	(0.022)	(0.025)	(0.006)
health_insured	0.088	0.306	0.178	0.294
	(0.231)	(0.134)	(0.174)	(0.043)
heart_disease	0.164	0.133	0.101	0.062
	(0.076)	(0.036)	(0.042)	(0.010)
arthritis	0.142	0.214	0.034	0.051
	(0.049)	(0.023)	(0.026)	(0.007)
stroke	0.219	0.183	0.035	0.130
	(0.107)	(0.055)	(0.076)	(0.015)
asthma	0.395	0.044	0.160	0.008
	(0.092)	(0.042)	(0.049)	(0.012)
	(0.144)	(0.072)	(0.072)	(0.020)
number_of_children2children	0.001	0.036	0.086	0.003
	(0.201)	(0.104)	(0.087)	(0.029)
number_of_children3children	0.082	0.103	0.182	0.057
	(0.366)	(0.184)	(0.169)	(0.051)
number_of_children4morechildren	1.373	1.216	0.273	0.037
	(1.393)	(0.616)	(0.384)	(0.115)
employment_statushomemaker	0.068	0.191	0.090	0.005
	(0.155)	(0.072)	(0.101)	(0.021)
employment_statusnoworkless1	0.410	0.359	0.016	0.044
	(0.527)	(0.275)	(0.278)	(0.082)
employment_statusnoworkmore1	0.201	0.159	0.078	0.252
	(0.359)	(0.181)	(0.193)	(0.048)
employment_statusretired	0.067	0.226	0.081	0.026
	(0.077)	(0.037)	(0.040)	(0.011)
employment_statusselfemployed	0.173	0.049	0.152	0.018
	(0.139)	(0.065)	(0.061)	(0.019)
employment_statusstudent		0.507	0.147	0.135
		(1.670)	(0.935)	(0.264)
employment_statusunable	0.427	0.298	0.054	0.192
	(0.103)	(0.055)	(0.080)	(0.015)
calculated_raceasian	0.012	0.242	1.014	0.063
	(0.406)	(0.201)	(0.167)	(0.047)
calculated_raceblack	0.031	0.006	0.488	0.078

	(0.083)	(0.040)	(0.051)	(0.011)
calculated_racenative	0.729	0.059	0.005	0.141
	(0.350)	(0.184)	(0.257)	(0.051)
calculated_raceother	0.136	0.020	0.177	0.056
	(0.430)	(0.236)	(0.259)	(0.069)
calculated_racepacific	10.366	0.480	0.527	0.212
	(119.466)	(1.310)	(1.797)	(0.350)
Constant	0.031	2.577	1.593	0.748
	(0.880)	(1.382)	(0.533)	(0.169)
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Survey Weights	Yes	Yes	Yes	Yes
Observations	9,318	37,070	51,855	51,855
Log Likelihood			73,484.660	98,678.670

Initial results for Model 1, as presented in Table 1, show great support for the paper's hypotheses (Table 1). Figure 1and Figure 2 are the model-estimated plots for respondents with diabetes education and those without diabetes education. Respondents who received diabetes education are represented by the blue curve (1), and those who did not are represented by the red curve (2).

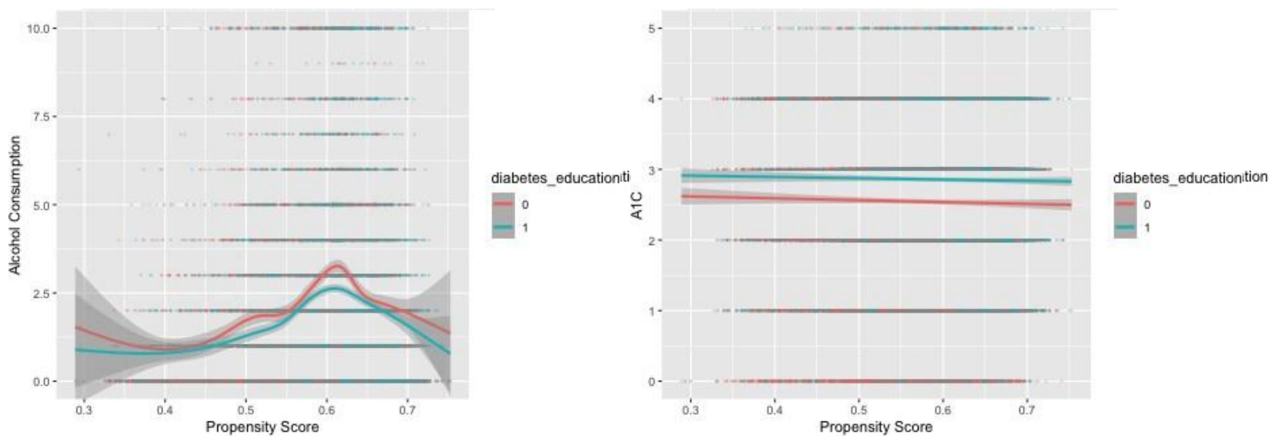

Figure 1: Regression Estimates Plot for Alcohol Consumption and A1C Checkups

Visually, it is clear that respondents in the treated group, those who have had diabetes education, perform better in all aspects of health. Given the 95% confidence interval, the two groups are also significantly different for most of the graphs shown. For risky behaviors, respondents without diabetes education consume more alcohol than respondents with diabetes education. They also show a higher probability of being a current smoker and less likely to exercise [5]. Further, respondents without diabetes education have more A1C check-ups than respondents with diabetes education.

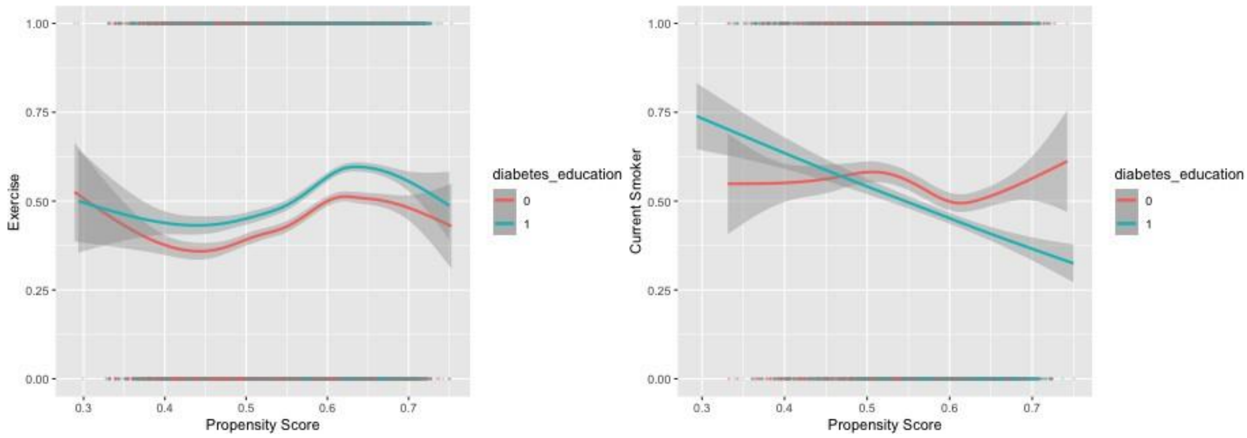

Figure 2: Regression Estimates Plot for Current Smokers and Physical Activity

Model 2

This sub-section is dedicated to General Health Models for dependent variables presented under Count data, including Physical Health and Mental Health. Physical and Mental Health represents the number of days respondents report their health to be NOT good during the past 30 days. In other words, these are the reported unhealthy mental and physical days,which can take the value ranging from 0 to 30. 0 represents respondents who do not haveany bad mental and/or physical health days, and 30 represents respondents who have the maximum of bad mental and/or physical health days out of a month.

Table 2: Regression Results for General Health Outcomes

Dependent variable: General Health Outcomes

	Mental Unhealthy Days	Physical Unhealthy Days
	Zero-Inflated NB	*Zero-Inflated NB*
	(1)	(2)
diabetes_education	0.030	0.035
	(0.021)	(0.014)
health_insured	0.128	0.223
	(0.121)	(0.085)
heart_disease	0.120	0.149
	(0.034)	(0.020)

arthritis	0.045	0.146
	(0.024)	(0.016)
stroke	0.086	0.167
	(0.048)	(0.031)
asthma	0.050	0.013
	(0.034)	(0.023)
bronchitis	0.053	0.165
	(0.036)	(0.024)
depression	0.513	0.154
	(0.023)	(0.018)
cancer	0.066	0.140
	(0.034)	(0.021)
calculated_age25to34	1.328	0.083
	(0.443)	(0.593)
calculated_age35to44	1.060	0.015
	(0.424)	(0.583)
calculated_age45to54	1.093	0.039
	(0.419)	(0.580)
calculated_age55to64	1.025	0.049
	(0.419)	(0.580)
calculated_age65older	1.064	0.078
	(0.420)	(0.580)
gendermale	0.111	0.100
	(0.023)	(0.016)
calculated_income15to25K	0.101	0.116
	(0.036)	(0.024)
calculated_income25to35K	0.096	0.090
	(0.040)	(0.027)
calculated_income35to50K	0.089	0.066
	(0.036)	(0.024)
calculated_incomele15K	0.093	0.143
	(0.047)	(0.032)
calculated_incomeothers	0.180	0.154
	(0.042)	(0.027)
calculated_educationattendCOL	0.158	0.089
	(0.027)	(0.019)
calculated_educationHSgrad	0.186	0.099
	(0.029)	(0.020)
calculated_educationK	0.285	0.171
	(0.051)	(0.034)
marital_statusdivorced	0.040	0.047
	(0.032)	(0.023)
marital_statusmembermarriedcoup	0.096	0.266
	(0.217)	(0.155)
marital_statusnevermarried	0.153	0.021

	(0.045)	(0.032)
marital_statusseparated	0.084	0.048
	(0.126)	(0.097)
marital_statuswidowed	0.013	0.007
	(0.030)	(0.020)
number_of_children1children	0.044	0.088
	(0.063)	(0.048)
number_of_children2children	0.084	0.300
	(0.087)	(0.072)
number_of_children3children	0.246	0.008
	(0.158)	(0.135)
number_of_children4morechildren	0.412	1.337
	(0.343)	(0.302)
employment_statushomemaker	0.092	0.276
	(0.069)	(0.047)
employment_statusnoworkless1	0.385	0.572
	(0.222)	(0.169)
employment_statusnoworkmore1	0.258	0.464
	(0.148)	(0.106)
employment_statusretired	0.029	0.303
	(0.037)	(0.025)
employment_statusselfemployed	0.255	0.108
	(0.075)	(0.049)
employment_statusstudent	1.212	0.920
	(0.721)	(1.068)
employment_statusunable	0.336	0.572
	(0.042)	(0.030)
calculated_raceasian	0.064	0.307
	(0.236)	(0.159)
calculated_raceblack	0.039	0.087
	(0.040)	(0.026)
calculated_racenative	0.069	0.053
	(0.174)	(0.125)
calculated_raceother	0.024	0.059
	(0.232)	(0.161)
calculated_racepacific	1.634	0.216
	(1.459)	(0.577)
Constant	0.701	1.923
	(0.441)	(0.588)
Month FE	Yes	Yes
Year FE	Yes	Yes
State FE	Yes	Yes
Demographics	Yes	Yes
Survey Weights	Yes	Yes

Observations	51,855	51,855
Log Likelihood	66,562.530	114,085.800

Initial results for Model 2, as shown in Table 2, indicate that diabetes education affects physical unhealthy days but not mental unhealthy days. Figure 3 is the model estimated plot for respondents' mental and physical unhealthy days, both with diabetes education and without. It is difficult to visualize the effect entirely. However, it is quite clear that respondents without diabetes education have more mental unhealthy days than respondents with diabetes education, especially those who have a higher propensity score.

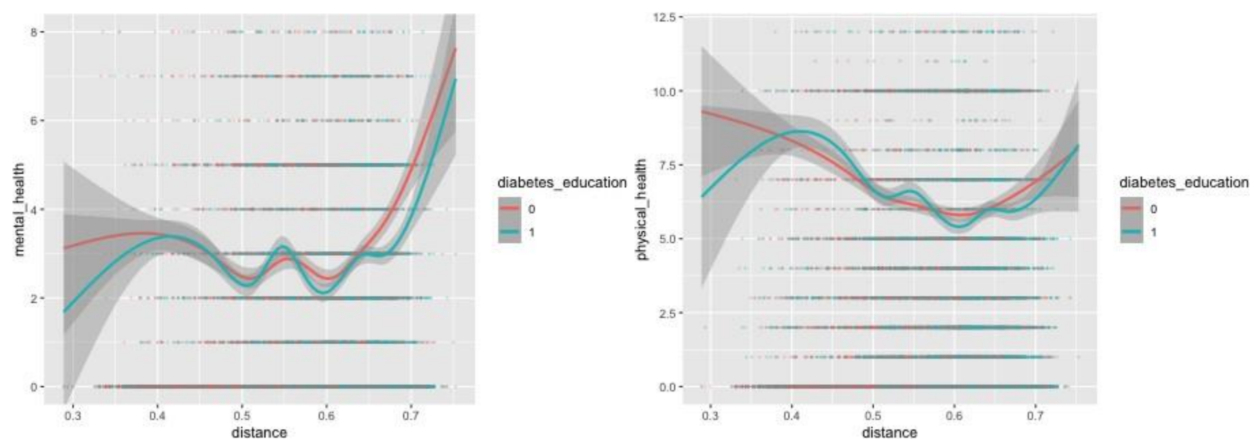

Figure 3: Regression Estimates Plot for Mental and Physical Unhealthy Days

The Economic Effects of the Estimates

Generally, it is quite difficult to pin down cost-saving estimates for probabilistic coefficients simply because there is no reference point to compare the percentage change to an actual number, especially for physical activity. For instance, given the positive effect of having diabetes education that yields an increase in the probability of exercising by 7.2%, it is not certain that the 7.2% increase in the likelihood of exercise translates to diabetes patients actually exercising. However, previous research has suggested that diabetes intervention by exercising can be cost-effective (Foster, 2011). Similarly, Coyle 2012 found that physical activity effectively treats diabetes and is also cost-saving effective. It also found that the cost-saving ranges depending on different types of exercising. In terms of total lifetime costs, life expectancy and quality-adjusted life expectancy were highest for the combined exercise program of aerobic training and resistance training (life-years = 11.79, QALYs = 8.94) compared with just aerobic training (life-years = 11.57, QALYs = 8.77), just resistance training (life-years = 11.51, QALYs = 8.73), and no program (life-years = 11.48, QALYs = 8.70).

The Count model is more straightforward to yield estimated cost savings for additional A1C check-ups because statistical models tend to interpret coefficients using addition increment. Chatterjee et al. estimate health system costs for screening and treating diabetes of 1,573 participants by risk group and percent cost difference for screening and treatment compared with no screening and shows that having A1C screening reduces health costs by 14.88 percent. Notably, without A1C screening, the health care cost is estimated at $95,710. Conversely, A1C screenings reduce this cost is to $81,467, a difference of $14,243. Coefficients produced by this paper suggest that having diabetes education increases the log odds of the number of doctor check-ups by 1.13 times among those who did not have A1C check-ups in the past 30 days. Meanwhile, having diabetes education increases the odds of having doctor check-ups by 2.51 times among those who had A1C check-ups in the past 30 days. These results indicate that for diabetic patients who have never had diabetes education, education would correlate to at least one additional A1C check-up and save the economy roughly $14,243 per person over three-year periods. This finding is economically significant, given that in this analysis alone, there are a total of 99,3288 observations with type 2 diabetes, of which 22,611 of them have not had diabetes education. It translates to the fact that, if all these observations have diabetes education and have at least one additional A1C check-up, they would havesaved the economy by roughly 322 million dollars.

Siegel et al. conducted a systematic literature review of studies from high-income countries evaluating the cost-effectiveness of interventions to manage diabetes recommended by the American Diabetes Association (ADA) and showed that having A1C screening would be very cost-effective. Remarkably, one relevant study by Gillett et al., 2015 shows that for adults aged 40–74 years with Prediabetes and undiagnosed Type 2 diabetes, compared to no A1C screening, having A1C screening would have an incremental cost-effectiveness ratio of $2,088/QALY (quality-adjusted life-year). Given that the sample only applies to adults from 40 to 74 years old this estimate is slightly lower than the calculations discussed above, however it still shows a significant effect on the economy.

Although the cost-benefit analysis in dollar terms of estimates yielded from this study is adequately explained, this study cannot find cost savings estimates in dollar terms of diabetes education on alcohol consumption. It could be due to ethical and moral reasons for why there have not been randomized control experiments regarding alcohol or smoking. However, it is not difficult to expect that reducing alcohol consumption and the rate of smoking by having diabetes education result in better savings, both physically and monetarily.

2. Conclusion

This study results support the vital role of diabetes education programs in promoting preventive health and health behaviors among diabetes patients. Specifically, although the study does not find a significant effect of diabetes education on mental health days, it shows strong evidence that receiving diabetes education reduces the number of days that the survey participants do not feel well physically. It also reduces respondent's alcohol intake and the probability of respondents being a current smoker. Moreover, this study also shows that having diabetes education increases the frequency of having an A1C check-up and increases physical activity among respondents.

Moreover, the cost-saving estimates yielded from this study demonstrates the essential part of diabetes education to health professionals and policymakers. Previous studies have repeatedly shown the effectiveness of diabetes intervention programs on saving money and increasing life expectancy. Although the results are widely different across different study designs and samples, results from this study give proper and reasonable cost-saving estimates for the economy using the national-level data and add to the recent literature on the economics of diabetes education. This study, solely based on just one specification regarding the impact of diabetes education on A1C doctor check-ups, concludes that just within the data used of 22,000 patients without diabetes education, the cost savings are estimated in the hundreds of millions of dollars. This number is expected to be much more extensive for different specifications with different covariates; perhaps it could reach billions of dollars saved for the economy each year.

While the study estimates are intensely investigated, there are several limitations to this study. First, since the BRFSS is a phone survey, it excludes patients in health institutions, including patients in nursing homes, patients who do not have a telephone, and people who have a severely impaired physical and mental illness that might not have been able to answer the survey. In addition, the survey does not have information on the level of A1C for each patient, which makes it impossible to investigate deeply into the effect of diabetes education on health based on different A1C levels. This missing piece is quite significant because previous literature has shown that people with different A1C levels impose different economic costs on society. Lastly, although the paper, using propensity score analysis, tries its best to get close to the causal estimates of diabetes education on health, the estimates are not causal if there is an endogeneity issue. People who have diabetes education tend to be more proactive, and if so, there would be an unobserved factor. Instrument variables could be used to solve, but again the BRFSS data is limited in term of non-health related variables. Thus, following an intensive search in the dataset, this paper cannot find the proper instruments to alleviate the endogeneity issue.

Nonetheless, the paper underscores the importance of diabetes education on various health factors. Furthermore, understanding diabetes education's implication on behavior and lifestyle is crucial to the cost-effective management of chronic illnesses such as diabetes. This paper helps shed light on scientific studies and helps motivate policymakers to focus on diabetes interventions that are widely accepted.

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