*Ernesto Ye Luo*

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*Drug Education Program and Short-term Substance Use Among High School Students in the United States*

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# 1. Introduction

Substance use among teenagers in the United States is a common phenomenon. By 12th grade, about two-thirds of students have tried alcohol.[[1]](#footnote-1) About half of 9th through 12th grade students reported ever having used marijuana.[[2]](#footnote-2) About 4 in 10 9th through 12th grade students reported having tried cigarettes.[[3]](#footnote-3) Among 12th graders, close to 2 in 10 reported using prescription medicine without a prescription.[[4]](#footnote-4) Experimenting with substances at a young age is associated with an increased risk for adult substance dependence, early pregnancy, and crime.[[5]](#footnote-5)

The U.S. Department of Education invested around US$2 billion in developing school-based drug education programs nationwide, with the goal of reducing substance use among high school students.[[6]](#footnote-6) Thus, in this study, I will explore the relationship between school-based drug education program and short-term substance use among high school students. Specifically, I will examine the following questions: Is there a causal relationship between school-based drug education programs and substance use among high school students in the United States? If so, how effective are drug education programs in preventing high school students from using substances?

# 2. Methods:

2.1 Sample

I conducted a case–control study to answer my research questions. The observational dataset that I analyzed is the 2012 National Survey on Drug Use and Health.[[7]](#footnote-7) The unit of the study is high school students (9th to 12 grade students). The final sample size of the dataset consists of 55,268 observations. However, my analysis only used 7,584 observations.

The distributions of race in the sample is relatively consistent with the distribution of the general U.S. population of secondary school students, as recorded by the 2009 National Center for Education Statistics data.[[8]](#footnote-8) The sample distribution consists of roughly 58% White students, 19% Hispanic students, 13% Black students, 5% Asian, 4% Pacific Islanders, and the remaining 1% of Native Americans and Mixed Race; this distribution is relatively consistent with 2009 National Center for Education Statistics data in that the population distribution consists 54% White students, 22% Hispanic students, 17% Black students, 5% Asian, and the remaining proportions being either Pacific Islanders, Native Americans, or Mixed Race.

The distribution of income in the sample is somewhat consistent with the distribution of the general U.S. population, as recorded by 2019 Congressional Research Service. In the sample, 48% of the general U.S. population had a yearly family income of $50,000 or less, while the distribution of the 2019 Congressional Research Service data consists of 37% of the general U.S. population having a yearly family income of $50,000 or less. It is important to keep in mind that the 11% discrepancy between the distributions in both datasets may be due to change of income overtime, as the sample was recorded in 2012 and the Congressional Research Service was recorded in 2019.

2.2 Procedures

The 2012 National Survey on Drug Use and Health recorded data of participants from all 50 states in the United States, including the District of Columbia. Participants were given $30 to answer online survey questions, facilitated by an interviewer. The dataset is a yearly accumulation of cross-sectional data from 2005 to 2012. The target population included civilian and non-institutionalized population of the United States. Roughly around 2% of the population who are institutionalized in the United States are not included in the survey. The survey data collection process is randomized by geographic regions; the 2012 National Survey on Drug Use and Health intentionally collected data from a minimum of 150 urban regions and 100 rural regions around the United States.

2.3 Measures

My analysis utilizes six main variables of interest from the 2012 National Survey on Drug Use and Health dataset: income, race, major depressive episode, attended school, drug education, and substance use. All six of these variables are categorical data type.

***Income***

The income variable measures the total family income of each participant. The income variable is binned into four levels: less than $20000, $20000-$49999, $50000-$74999, and $75000 and more.

***Race***

The race variable consisted of seven levels: Non-Hispanic White, Non-Hispanic Black, Non-Hispanic Native American, Non-Hispanic Pacific Islander, Non-Hispanic Asian, Non-Hispanic More than One Race, and Hispanic.

***Major Depressive Episode***

The major depressive episode variable measures whether or not the participant has self-reported of experiencing a major depressive episode within the past 12 months.

***Attended School***

The attended school variable measures whether or not the participant has self-reported of attending any type of school within the past 12 months.

***Drug Education (Treatment Variable)***

The drug education variable measures whether or not the participant has self-reported of receiving any form of school-based drug education program within the past 12 months. This includes listening to a lecture about drugs, engaging in a discussion about drugs, or watching a film about drugs in class.

***Substance Use (Response Variable)***

The substance use variable measures whether or not the participant has self-reported of using any form of substance within the past 12 months illicitly. Substance includes the following: tobacco, alcohol, marijuana, cocaine, crack, heroin, hallucinogen, inhalant, pain reliever, tranquilizer, stimulant, and sedative. I define the use of substances in the past 12 months as short-term substance use.

2.4 Matching

One way to establish causality is to conduct a randomized trial on a research question of interest. I implemented Matching to emulate a randomized trial. There are three key steps needed to implement Matching: 1) layout a model with all relevant covariates, 2) choose the appropriate treatment group to match to, and 3) use Greedy Matching to match the most similar observations for treatment and control groups.

First, implementing Matching requires identifying relevant covariates that may affect who receives drug education program within the past 12 months. There are four covariates that may affect who receives drug education program within the past 12 months: income, race, major depressive episode, and attended school. First, income is an important variable to consider because students with low socio-economic backgrounds are less likely to attend classes because they tend to be overwhelmed with problems at home and in their community, and thus they might miss sessions of when schools discuss about drug prevention. Second, race is associated with a greater likelihood of skipping classes because students of color (particularly Black students) do not feel like they belong due to experiencing racial bias in school;[[9]](#footnote-9) one would more likely miss class sessions about drugs when one skips classes. Third, experiencing major depressive episode within the past 12 months may undermine one’s interest in school since one key symptom of major depression is a lack of interest in anything. One’s lack of interest in school may prompt one to skip classes, and thereby miss class sessions about drugs. Lastly, attending a school within the past 12 months is a prerequisite to receiving a school-based drug education program. Figure 1.1 entails a theoretical model with the aforementioned covariates.

Income Race

Drug Education Substance Use

Major Depression Attended School

*Figure 1.1: theoretical model for testing causality between drug education and substance use with covariates.*

# Next, implementing Matching requires choosing the appropriate treatment group to match to. As shown in Figure 1.2, there are greater proportions of participants who have received drug education than not. Hence, the appropriate treatment group to match to should be those who have not received drug education because they have fewer proportion. Consequently, my statistical analysis would also have to reflect on the appropriate treatment group assignment.

Chart, bar chart

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*Figure 1.2: there are greater proportions of participants who have received drug education than not.*

Lastly, I used the Greedy Matching to match the most similar observations for treatment and control groups. I assessed the adequacy of the Greedy Match implementation by using Mahalanobis distance. The Mahalanobis distance calculates the standardized mean difference (smd) of each covariate, which indicates how adequately matched the relevant covariates are. The standard of adequacy for matching is a smd value of 0.2. In other words, if a covariate has a value of below 0.2, then it is adequately matched. Otherwise, the covariate is not adequately matched. All covariates must match adequately in order to meaningfully establish causality.

2.5 Statistical Analysis

Since both my treatment and response variables are binary categorical data types, I used the McNemar’s test to conduct my statistical analysis. The McNemar’s test tests for statistical significance, provides an average treatment effect estimation that is measured in odds ratio, and shows the 95% Confidence Interval of the treatment effect. Because the treatment entails those who did not receive drug education, the conclusion of my statistical analysis would have to focus on what the effect of not receiving drug education has on substance use.

# 3. Results:

Greedy Matching is effective in creating balance between treatment and control groups. All four covariates have a smd value of below 0.2 after Matching as shown in Figure 1.3. Thus, it is possible to emulate a randomized trial in order to establish causality.

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*Figure 1.3: Standardized mean values of each of the four covariates after implementing Greedy Matching.*

The McNemar’s test on Figure 1.4 reveals that receiving drug education program has a significant causal relationship with the likelihood of using substances (p-value < 0.05). Specifically, those who did not receive the treatment (drug education program) have an odds of using substance in the short-term that is 1.24 times higher on average than those who are on treatment (95% CI: 1.09 to 1.41), while assuming that the control factors adequately express the causal structure. Therefore, receiving drug education program is effective in decreasing the likelihood of high school students using substances in the short-term.

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*Figure 1.4: McNemar’s test on the relationship between not receiving drug education program on substance use.*

# 4. Discussion:

4.1 Limitations

My analysis assumes that all appropriate time has passed for researcher to be able to adequately assess whether or not drug education program has been effective in reducing the likelihood of high school students using substances. However, this assumption does not necessarily hold true with the dataset I analyzed with. Recall that the treatment variable measures whether or not the participant has received a drug education program in the past 12 months. Hence, the measurement of this variable does not entail that a participant must have received the drug education program in the beginning of the past 12 months. It could have been the case that a participant has received the drug education program a day before filling out the survey for the dataset. This possibility can undermine my analysis in the sense that, in the worst-case scenario, a good proportion of participants have received drug education program in the later parts of the past 12 months. Thus, one may argue that my analysis is severely limited by its inability to rule out that possibility that not enough time has passed to adequately assess whether or not drug education program is effective in reducing the likelihood of high school students using substances.

Next, my analysis does not distinguish between students coming from middle-class backgrounds or upper-class backgrounds. Recall that the income variable only measures four levels of income brackets (less than $20000, $20000-$49999, $50000-$74999, and $75000 and more). The highest income bracket of $75000 and more does not distinguish individuals whose family earn a lot more than $75000 (for instance, $200000). Hence, there is a possibility that a good proportion of participants in this bracket has a yearly family income of way above $75000, which is not representative of the general U.S. population’s family income. As a result, this uncertainty raises concern of a possible estimated bias in my model.

Lastly, my analysis assumes that my model has accounted for all relevant variables. However, this is not necessarily the case. The literature indicates that geographic regional differences can also play a role in whether or not someone receives a drug education program.[[10]](#footnote-10) The dataset I analyzed does not have a variable that measures geographic regional differences.

4.2 Implications

To mitigate the limitations I have pointed out, one can design a future study that conducts a completely randomized experiment on the research questions I posed. The study would randomly select which high school student receives drug education program and which high school student does not from the general U.S. population. Then, researchers can follow up with each high school student after one year and ask whether or not they have used substances (assuming that one year is an adequate definition of short-term substance use). Thus, this can mitigate the limitation of assuming that all appropriate time has passed for researcher to be able to adequately assess whether or not drug education program has been effective in reducing the likelihood of high school students using substances because one would know for sure that all high school students are followed-up after a year from the experimental design. This design can also mitigate the last two limitations by ensuring that one captures a robust random sample of the general U.S. population.

Alternatively, one can also design a future study that conducts another case-control study on the research questions I posed, with a more specific data collection design. The dataset would have to specifically ask whether or not the participant has received a drug education program from six months to a year prior (assuming that six months to a year prior still has an effect on using substance use). It would also have to ask whether the participants have used substances ever since they have received the drug education program. Hence, this more specific data collection design would mitigate the first limitation in that one can be more certain that enough time has passed to adequately assess the treatment effect. To mitigate the last two limitations, one can design a question that captures a more diverse stratification of income bracket levels and include a question that asks specifically what geographic region the participant is from in the United States.

Despite the severe limitations in my analysis, my findings can still serve as confirmation for the notion that receiving drug education program is generally effective in reducing the likelihood of high school students using substances in the United States. To improve the reliability of this notion that receiving drug education program is generally effective in reducing the likelihood of high school students using substances in the United States, researchers would need to bring my findings into conversation with other similar studies. If there is a majority consensus of the same result when accounting for all findings, then one can more decisively conclude that receiving drug education program is generally effective in reducing the likelihood of high school students using substances in the United States. On the other hand, if there is no majority consensus, then it is more difficult to draw conclusions about the effectiveness of drug education program in reducing the likelihood of high school students using substances in the United States.

# 5. Appendix:

load("34933-0001-Data.rda")

require(tidyverse)

## Loading required package: tidyverse

## ── Attaching packages ─────────────────────────────────────── tidyverse 1.3.1 ──

## ✓ ggplot2 3.3.5 ✓ purrr 0.3.4  
## ✓ tibble 3.1.6 ✓ dplyr 1.0.8  
## ✓ tidyr 1.1.4 ✓ stringr 1.4.0  
## ✓ readr 2.1.1 ✓ forcats 0.5.1

## ── Conflicts ────────────────────────────────────────── tidyverse\_conflicts() ──  
## x dplyr::filter() masks stats::filter()  
## x dplyr::lag() masks stats::lag()

require(ggplot2)  
require(qacBase)

## Loading required package: qacBase

require(vcd)

## Loading required package: vcd

## Loading required package: grid

require(tableone)

## Loading required package: tableone

require(Matching)

## Loading required package: Matching

## Loading required package: MASS

##   
## Attaching package: 'MASS'

## The following object is masked from 'package:dplyr':  
##   
## select

## ##   
## ## Matching (Version 4.10-8, Build Date: 2022-11-03)  
## ## See http://sekhon.berkeley.edu/matching for additional documentation.  
## ## Please cite software as:  
## ## Jasjeet S. Sekhon. 2011. ``Multivariate and Propensity Score Matching  
## ## Software with Automated Balance Optimization: The Matching package for R.''  
## ## Journal of Statistical Software, 42(7): 1-52.   
## ##

library(exact2x2)

## Loading required package: exactci

## Loading required package: ssanv

## Loading required package: testthat

##   
## Attaching package: 'testthat'

## The following object is masked from 'package:dplyr':  
##   
## matches

## The following object is masked from 'package:purrr':  
##   
## is\_null

## The following objects are masked from 'package:readr':  
##   
## edition\_get, local\_edition

## The following object is masked from 'package:tidyr':  
##   
## matches

### Selecting Variables of Interest

df <- da34933.0001 %>%  
 dplyr::select(IREDUC2, ANYEDUC3, INCOME, NEWRACE2, YMDEYR, YEATNDYR,  
 IRCIGRC,  
 IRCGRRC,  
 IRSLTRC,  
 IRALCRC,  
 IRMJRC,  
 IRCOCRC,  
 IRCRKRC,  
 IRHERRC,  
 IRHALRC,  
 IRINHRC,  
 IRANLRC,  
 IRTRNRC,  
 IRSTMRC,  
 IRSEDRC  
 ) %>%  
 filter(IREDUC2 %in% c("(5) Ninth grade", "(6) Tenth grade", "(7) Eleventh grade", "(8) Twelfth grade"))

### Recoding Substance Use Variables (1 if the participant used any substance and 0 if participant did not use any substance)

df <- df %>%  
 mutate(usedSubstance = ifelse(IRCIGRC == "(1) Within the past 30 days"   
 | IRCIGRC == "(2) More than 30 days ago but within the past 12 mos"   
 | IRCGRRC == "(1) Within the past 30 days"   
 | IRCGRRC == "(2) More than 30 days ago but within the past 12 mos"   
 | IRSLTRC == "(1) Within the past 30 days"   
 | IRSLTRC == "(2) More than 30 days ago but within the past 12 mos"   
 | IRALCRC == "(1) Within the past 30 days"   
 | IRALCRC == "(2) More than 30 days ago but within the past 12 mos"  
 | IRMJRC == "(1) Within the past 30 days"  
 | IRMJRC == "(2) More than 30 days ago but within the past 12 mos"  
 | IRCOCRC == "(1) Within the past 30 days"  
 | IRCOCRC == "(2) More than 30 days ago but within the past 12 mos"  
 | IRCRKRC == "(1) Within the past 30 days"  
 | IRCRKRC == "(2) More than 30 days ago but within the past 12 mos"  
 | IRHERRC == "(1) Within the past 30 days"  
 | IRHERRC == "(2) More than 30 days ago but within the past 12 mos"  
 | IRHALRC == "(1) Within the past 30 days"  
 | IRHALRC == "(2) More than 30 days ago but within the past 12 mos"  
 | IRINHRC == "(1) Within the past 30 days"  
 | IRINHRC == "(2) More than 30 days ago but within the past 12 mos"  
 | IRANLRC == "(1) Within the past 30 days"  
 | IRANLRC == "(2) More than 30 days ago but within the past 12 mos"  
 | IRTRNRC == "(1) Within the past 30 days"  
 | IRTRNRC == "(2) More than 30 days ago but within the past 12 mos"  
 | IRSTMRC == "(1) Within the past 30 days"  
 | IRSTMRC == "(2) More than 30 days ago but within the past 12 mos"  
 | IRSEDRC == "(1) Within the past 30 days"  
 | IRSEDRC == "(2) More than 30 days ago but within the past 12 mos"  
 , 1, 0))

### Discard specific substance variables

df <- df %>%  
 dplyr::select(-c(IREDUC2,  
 IRCIGRC,  
 IRCGRRC,  
 IRSLTRC,  
 IRALCRC,  
 IRMJRC,  
 IRCOCRC,  
 IRCRKRC,  
 IRHERRC,  
 IRHALRC,  
 IRINHRC,  
 IRANLRC,  
 IRTRNRC,  
 IRSTMRC,  
 IRSEDRC))

### Delete variables with NAs

df <- na.omit(df)

### Proportion of participants that used substances

table(df$usedSubstance)

##   
## 0 1   
## 3588 3996

### Received education (0 if participant received drug education and 1 if participant did not receive drug education)

df <- df %>%  
 mutate(ANYEDUC3 = ifelse(ANYEDUC3 == "(1) Yes (YEDECLAS=1 or YEDERGLR=1 or YEDESPCL=1)", 0, 1))

### Recode all covarites to numeric

df$INCOME <- as.numeric(df$INCOME)  
  
df$INCOME[df$INCOME == 1] <- 0  
df$INCOME[df$INCOME == 2] <- 1  
df$INCOME[df$INCOME == 3] <- 2  
df$INCOME[df$INCOME == 4] <- 3  
  
  
df$NEWRACE2 <- as.numeric(df$NEWRACE2)  
  
df$NEWRACE2[df$NEWRACE2 == 1] <- 0  
df$NEWRACE2[df$NEWRACE2 == 2] <- 1  
df$NEWRACE2[df$NEWRACE2 == 3] <- 2  
df$NEWRACE2[df$NEWRACE2 == 4] <- 3  
df$NEWRACE2[df$NEWRACE2 == 5] <- 4  
df$NEWRACE2[df$NEWRACE2 == 6] <- 5  
df$NEWRACE2[df$NEWRACE2 == 7] <- 6  
  
  
df$YMDEYR <- as.numeric(df$YMDEYR)  
  
df$YMDEYR[df$YMDEYR == 1] <- 1  
df$YMDEYR[df$YMDEYR == 2] <- 0  
  
  
  
df$YEATNDYR <- as.numeric(df$YEATNDYR)  
  
df$YEATNDYR[df$YEATNDYR == 1] <- 1  
df$YEATNDYR[df$YEATNDYR == 2] <- 0

### Rename all non-response variables

df <- df %>%  
 rename(  
 DrugEducation = ANYEDUC3,  
 Income = INCOME,  
 Race = NEWRACE2,  
 MajorDepression = YMDEYR,  
 AttendedSchool = YEATNDYR  
 )

### Proportions of participants who have received drug education program in the past 12 months.

tab(df, DrugEducation, plot=TRUE)

Chart

Description automatically generated

### Proportions of participants’ income.

tab(df, Income, plot=TRUE)

Chart, bar chart

Description automatically generated

### Proportions of participants’ race.

tab(df, Race, plot=TRUE)

Chart, bar chart

Description automatically generated

### Proportions of participants who experience major depressive episode in the past 12 months.

tab(df, MajorDepression, plot=TRUE)

Chart, histogram

Description automatically generated

### Proportions of participants who attended school in the past 12 months.

tab(df, AttendedSchool, plot=TRUE)

Chart

Description automatically generated

### Assessing Balance Before Matching

xvars <- c("Income", "Race", "MajorDepression", "AttendedSchool")  
  
table1 <- CreateTableOne(vars=xvars, strata="DrugEducation", data=df, test=FALSE)  
  
print(table1, smd=TRUE)

## Stratified by DrugEducation  
## 0 1 SMD   
## n 5477 2107   
## Income (mean (SD)) 1.73 (1.11) 1.60 (1.10) 0.113  
## Race (mean (SD)) 1.73 (2.47) 1.65 (2.43) 0.032  
## MajorDepression (mean (SD)) 0.13 (0.33) 0.13 (0.34) 0.016  
## AttendedSchool (mean (SD)) 1.00 (0.04) 0.99 (0.10) 0.112

### Assessing Balance After Matching

set.seed(6666)  
greedymatch <- Match(Tr=df$DrugEducation, M=1, X=df[xvars], replace=FALSE)  
  
matched <- df[unlist(greedymatch[c("index.treated", "index.control")]), ]  
  
  
matchedtab1 <- CreateTableOne(vars=xvars, strata="DrugEducation",  
 data=matched, test=FALSE)  
  
print(matchedtab1, smd = TRUE)

## Stratified by DrugEducation  
## 0 1 SMD   
## n 2107 2107   
## Income (mean (SD)) 1.60 (1.10) 1.60 (1.10) 0.002  
## Race (mean (SD)) 1.66 (2.43) 1.65 (2.43) 0.003  
## MajorDepression (mean (SD)) 0.13 (0.34) 0.13 (0.34) <0.001  
## AttendedSchool (mean (SD)) 1.00 (0.06) 0.99 (0.10) 0.077

### Statistical Analysis (McNemar Test)

y\_trt <- matched$usedSubstance[matched$DrugEducation == 1]  
y\_con <- matched$usedSubstance[matched$DrugEducation == 0]  
  
  
mcnemar.exact(table(y\_con, y\_trt))

##   
## Exact McNemar test (with central confidence intervals)  
##   
## data: table(y\_con, y\_trt)  
## b = 545, c = 440, p-value = 0.0009114  
## alternative hypothesis: true odds ratio is not equal to 1  
## 95 percent confidence interval:  
## 1.090408 1.407636  
## sample estimates:  
## odds ratio   
## 1.238636

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