

# Analysing the effects of higher education on voters' preferences

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github: <https://github.com/Amyzhongkinu/STA304-Final-Project>

## Abstract

In this study, the dataset retrieved from Democracy Fund Voter Study Group was used to investigate how propensity score matching is used to make causal inferences between higher education and voting preferences of voters for 2020 U.S. presidential election. Although there are some bias in propensity score matching, the results of the propensity score model indicated that highly educated voters are more likely to choose Biden as the next president of the United States.

## Keywords

Key words: Propensity Score, Causal Inference, Higher education, President election

## Introduction

Today, people who receive higher education generally have more opportunities for jobs and higher overall quality of life. They might have realized the benefits of higher education and thus may be more concerned about this field. Policies formulated by the president, such as cutting college costs, play a very important role in the development of higher education. People who care about higher education might vote for the one that will advance a comprehensive higher education agenda.

The purpose of this project is to analyze the effects of higher education on voters' preferences for candidates of U.S. Presidential election 2020. Firstly, data retrieved from Democracy Fund Voter Study Group will be organized by Propensity Score Matching. To be more specific, treated and controlled observations will be matched on the estimated probability of being treated while the treatment is the higher education. Then, a logistic regression model with age, gender, household income, employment, state, race\_ethnicity, and higher education assumed as correlated variables will be conducted to see whether this treatment is statistically significant. If the answer is yes, then we will be able to make a causal inference that voters with higher education levels are more likely or less likely to choose Biden as the next U.S. president.

The following sections explain how to use propensity score matching to make causal inferences between higher education and voting preferences. The data, propensity score matching method and propensity score analysis model will be described in the "Methodology" section. The analysis results will be provided in the "Results" section, and the causal inferences and conclusions of the data will be provided in the "Conclusions" section.

## Methodology

### Data:

The dataset is obtained from Democracy Foundation + UCLA Nationscape survey data (2020) conducted by Democracy Foundation + UCLA Nationscape. The Democracy Foundation + UCLA Nationscape survey data (2020) was collected by interviewing people in almost every county, congressional district, and medium-sized city in the United States before the 2020 U.S. presidential election. There are 6,479 observations in the dataset and 265 variables. Not all variables are needed, so only a few of them are selected for this project. The selected variables and their categories are shown in the following table.

variable	category
Age	discrete
Registration	categorical
Vote_intention	categorical
Vote_2020	categorical
Gender	categorical
Race_ethnicity	categorical
Education	categorical
Employment	categorical
State	categorical
household_income	categorical

Table.1

		Stratified by edu_high
		0
##	n	3132
##	registration (%)	
##	Registered	2514 (80.3)
##	Not registered	522 (16.7)
##	Don't know	96 ( 3.1)
##	vote_intention (%)	
##	Yes, I will vote	2430 (77.6)
##	No, I will not vote but I am eligible	333 (10.6)
##	No, I am not eligible to vote	0 ( 0.0)
##	Not sure	369 (11.8)
##	vote_2020 (%)	
##	Donald Trump	1199 (38.3)
##	Joe Biden	1247 (39.8)
##	Someone else	140 ( 4.5)
##	I would not vote	197 ( 6.3)
##	I am not sure/don't know	349 (11.1)
##	age (mean (SD))	43.85 (17.33)
##	gender = Male (%)	1411 (45.1)
##	race_ethnicity (%)	
##	White	2256 (72.0)
##	Black, or African American	451 (14.4)
##	American Indian or Alaska Native	47 ( 1.5)
##	Asian (Asian Indian)	33 ( 1.1)
##	Asian (Chinese)	20 ( 0.6)
##	Asian (Filipino)	11 ( 0.4)
##	Asian (Japanese)	4 ( 0.1)
##	Asian (Korean)	5 ( 0.2)
##	Asian (Vietnamese)	3 ( 0.1)
##	Asian (Other)	15 ( 0.5)
##	Pacific Islander (Native Hawaiian)	7 ( 0.2)
##	Pacific Islander (Guamanian)	0 ( 0.0)
##	Pacific Islander (Samoan)	2 ( 0.1)
##	Pacific Islander (Other)	6 ( 0.2)
##	Some other race	272 ( 8.7)
##	education (%)	
##	3rd Grade or less	11 ( 0.4)
##	Middle School - Grades 4 - 8	19 ( 0.6)

##	Completed some high school	552 (17.6)
##	High school graduate	904 (28.9)
##	Other post high school vocational training	297 ( 9.5)
##	Completed some college, but no degree	1214 (38.8)
##	Associate Degree	0 ( 0.0)
##	College Degree (such as B.A., B.S.)	0 ( 0.0)
##	Completed some graduate, but no degree	0 ( 0.0)
##	Masters degree	0 ( 0.0)
##	Doctorate degree	135 ( 4.3)
##	employment (%)	
##	Full-time employed	925 (29.5)
##	Homemaker	243 ( 7.8)
##	Retired	549 (17.5)
##	Unemployed or temporarily on layoff	383 (12.2)
##	Part-time employed	339 (10.8)
##	Permanently disabled	224 ( 7.2)
##	Student	179 ( 5.7)
##	Self-employed	232 ( 7.4)
##	Other:	58 ( 1.9)
##	state (%)	
##	AK	7 ( 0.2)
##	AL	51 ( 1.6)
##	AR	27 ( 0.9)
##	AZ	81 ( 2.6)
##	CA	341 (10.9)
##	CO	50 ( 1.6)
##	CT	25 ( 0.8)
##	DC	9 ( 0.3)
##	DE	20 ( 0.6)
##	FL	228 ( 7.3)
##	GA	92 ( 2.9)
##	HI	11 ( 0.4)
##	IA	32 ( 1.0)
##	ID	17 ( 0.5)
##	IL	135 ( 4.3)
##	IN	71 ( 2.3)
##	KS	22 ( 0.7)
##	KY	52 ( 1.7)
##	LA	44 ( 1.4)
##	MA	47 ( 1.5)
##	MD	42 ( 1.3)
##	ME	10 ( 0.3)
##	MI	84 ( 2.7)
##	MN	23 ( 0.7)
##	MO	76 ( 2.4)
##	MS	24 ( 0.8)
##	MT	7 ( 0.2)
##	NC	117 ( 3.7)
##	ND	3 ( 0.1)
##	NE	6 ( 0.2)
##	NH	10 ( 0.3)
##	NJ	81 ( 2.6)
##	NM	16 ( 0.5)
##	NV	33 ( 1.1)

##	NY	196 ( 6.3)		
##	OH	153 ( 4.9)		
##	OK	39 ( 1.2)		
##	OR	53 ( 1.7)		
##	PA	126 ( 4.0)		
##	RI	9 ( 0.3)		
##	SC	58 ( 1.9)		
##	SD	6 ( 0.2)		
##	TN	70 ( 2.2)		
##	TX	257 ( 8.2)		
##	UT	28 ( 0.9)		
##	VA	79 ( 2.5)		
##	VT	9 ( 0.3)		
##	WA	65 ( 2.1)		
##	WI	57 ( 1.8)		
##	WV	29 ( 0.9)		
##	WY	4 ( 0.1)		
##	household_income (%)			
##	Less than \$14,999	738 (23.6)		
##	\$15,000 to \$19,999	230 ( 7.3)		
##	\$20,000 to \$24,999	232 ( 7.4)		
##	\$25,000 to \$29,999	215 ( 6.9)		
##	\$30,000 to \$34,999	190 ( 6.1)		
##	\$35,000 to \$39,999	185 ( 5.9)		
##	\$40,000 to \$44,999	140 ( 4.5)		
##	\$45,000 to \$49,999	149 ( 4.8)		
##	\$50,000 to \$54,999	157 ( 5.0)		
##	\$55,000 to \$59,999	80 ( 2.6)		
##	\$60,000 to \$64,999	80 ( 2.6)		
##	\$65,000 to \$69,999	61 ( 1.9)		
##	\$70,000 to \$74,999	87 ( 2.8)		
##	\$75,000 to \$79,999	82 ( 2.6)		
##	\$80,000 to \$84,999	39 ( 1.2)		
##	\$85,000 to \$89,999	25 ( 0.8)		
##	\$90,000 to \$94,999	32 ( 1.0)		
##	\$95,000 to \$99,999	47 ( 1.5)		
##	\$100,000 to \$124,999	129 ( 4.1)		
##	\$125,000 to \$149,999	77 ( 2.5)		
##	\$150,000 to \$174,999	37 ( 1.2)		
##	\$175,000 to \$199,999	26 ( 0.8)		
##	\$200,000 to \$249,999	54 ( 1.7)		
##	\$250,000 and above	40 ( 1.3)		
##	edu_high = 1 (%)	0 ( 0.0)		
##	.fitted (mean (SD))	0.36 (0.20)		
##	treated (mean (SD))	0.00 (0.00)		
##	match.ind (mean (SD))	3228.01 (1887.97)		
##	cnts (mean (SD))	0.86 (0.35)		
##	pairs (mean (SD))	1347.50 (777.84)		
##		Stratified by edu_high		
##		1	p	test
##	n	2694		
##	registration (%)			<0.001
##	Registered	2529 ( 93.9)		
##	Not registered	142 ( 5.3)		

##	Don't know	23 ( 0.9)	
##	vote_intention (%)		NaN
##	Yes, I will vote	2477 ( 91.9)	
##	No, I will not vote but I am eligible	110 ( 4.1)	
##	No, I am not eligible to vote	0 ( 0.0)	
##	Not sure	107 ( 4.0)	
##	vote_2020 (%)		<0.001
##	Donald Trump	1100 ( 40.8)	
##	Joe Biden	1250 ( 46.4)	
##	Someone else	89 ( 3.3)	
##	I would not vote	57 ( 2.1)	
##	I am not sure/don't know	198 ( 7.3)	
##	age (mean (SD))	47.73 (15.40)	<0.001
##	gender = Male (%)	1492 ( 55.4)	<0.001
##	race_ethnicity (%)		<0.001
##	White	2140 ( 79.4)	
##	Black, or African American	238 ( 8.8)	
##	American Indian or Alaska Native	28 ( 1.0)	
##	Asian (Asian Indian)	44 ( 1.6)	
##	Asian (Chinese)	45 ( 1.7)	
##	Asian (Filipino)	25 ( 0.9)	
##	Asian (Japanese)	12 ( 0.4)	
##	Asian (Korean)	8 ( 0.3)	
##	Asian (Vietnamese)	9 ( 0.3)	
##	Asian (Other)	15 ( 0.6)	
##	Pacific Islander (Native Hawaiian)	3 ( 0.1)	
##	Pacific Islander (Guamanian)	1 ( 0.0)	
##	Pacific Islander (Samoan)	0 ( 0.0)	
##	Pacific Islander (Other)	1 ( 0.0)	
##	Some other race	125 ( 4.6)	
##	education (%)		<0.001
##	3rd Grade or less	0 ( 0.0)	
##	Middle School - Grades 4 - 8	0 ( 0.0)	
##	Completed some high school	0 ( 0.0)	
##	High school graduate	0 ( 0.0)	
##	Other post high school vocational training	0 ( 0.0)	
##	Completed some college, but no degree	0 ( 0.0)	
##	Associate Degree	517 ( 19.2)	
##	College Degree (such as B.A., B.S.)	1363 ( 50.6)	
##	Completed some graduate, but no degree	207 ( 7.7)	
##	Masters degree	607 ( 22.5)	
##	Doctorate degree	0 ( 0.0)	
##	employment (%)		<0.001
##	Full-time employed	1478 ( 54.9)	
##	Homemaker	79 ( 2.9)	
##	Retired	475 ( 17.6)	
##	Unemployed or temporarily on layoff	181 ( 6.7)	
##	Part-time employed	189 ( 7.0)	
##	Permanently disabled	70 ( 2.6)	
##	Student	55 ( 2.0)	
##	Self-employed	149 ( 5.5)	
##	Other:	18 ( 0.7)	
##	state (%)		<0.001
##	AK	1 ( 0.0)	

##	AL	33 ( 1.2)	
##	AR	15 ( 0.6)	
##	AZ	68 ( 2.5)	
##	CA	309 ( 11.5)	
##	CO	34 ( 1.3)	
##	CT	42 ( 1.6)	
##	DC	11 ( 0.4)	
##	DE	4 ( 0.1)	
##	FL	211 ( 7.8)	
##	GA	75 ( 2.8)	
##	HI	15 ( 0.6)	
##	IA	19 ( 0.7)	
##	ID	10 ( 0.4)	
##	IL	128 ( 4.8)	
##	IN	42 ( 1.6)	
##	KS	25 ( 0.9)	
##	KY	27 ( 1.0)	
##	LA	31 ( 1.2)	
##	MA	57 ( 2.1)	
##	MD	48 ( 1.8)	
##	ME	10 ( 0.4)	
##	MI	80 ( 3.0)	
##	MN	39 ( 1.4)	
##	MO	37 ( 1.4)	
##	MS	20 ( 0.7)	
##	MT	9 ( 0.3)	
##	NC	72 ( 2.7)	
##	ND	3 ( 0.1)	
##	NE	13 ( 0.5)	
##	NH	8 ( 0.3)	
##	NJ	107 ( 4.0)	
##	NM	9 ( 0.3)	
##	NV	33 ( 1.2)	
##	NY	277 ( 10.3)	
##	OH	110 ( 4.1)	
##	OK	21 ( 0.8)	
##	OR	32 ( 1.2)	
##	PA	118 ( 4.4)	
##	RI	2 ( 0.1)	
##	SC	39 ( 1.4)	
##	SD	9 ( 0.3)	
##	TN	34 ( 1.3)	
##	TX	175 ( 6.5)	
##	UT	16 ( 0.6)	
##	VA	103 ( 3.8)	
##	VT	5 ( 0.2)	
##	WA	51 ( 1.9)	
##	WI	48 ( 1.8)	
##	WV	8 ( 0.3)	
##	WY	1 ( 0.0)	
##	household_income (%)		<0.001
##	Less than \$14,999	141 ( 5.2)	
##	\$15,000 to \$19,999	78 ( 2.9)	
##	\$20,000 to \$24,999	79 ( 2.9)	

##	\$25,000 to \$29,999	105 ( 3.9)	
##	\$30,000 to \$34,999	130 ( 4.8)	
##	\$35,000 to \$39,999	98 ( 3.6)	
##	\$40,000 to \$44,999	95 ( 3.5)	
##	\$45,000 to \$49,999	110 ( 4.1)	
##	\$50,000 to \$54,999	167 ( 6.2)	
##	\$55,000 to \$59,999	84 ( 3.1)	
##	\$60,000 to \$64,999	87 ( 3.2)	
##	\$65,000 to \$69,999	65 ( 2.4)	
##	\$70,000 to \$74,999	97 ( 3.6)	
##	\$75,000 to \$79,999	98 ( 3.6)	
##	\$80,000 to \$84,999	71 ( 2.6)	
##	\$85,000 to \$89,999	66 ( 2.4)	
##	\$90,000 to \$94,999	40 ( 1.5)	
##	\$95,000 to \$99,999	102 ( 3.8)	
##	\$100,000 to \$124,999	323 ( 12.0)	
##	\$125,000 to \$149,999	237 ( 8.8)	
##	\$150,000 to \$174,999	140 ( 5.2)	
##	\$175,000 to \$199,999	89 ( 3.3)	
##	\$200,000 to \$249,999	99 ( 3.7)	
##	\$250,000 and above	93 ( 3.5)	
##	edu_high = 1 (%)	2694 (100.0)	<0.001
##	.fitted (mean (SD))	0.58 (0.20)	<0.001
##	treated (mean (SD))	1.00 (0.00)	<0.001
##	match.ind (mean (SD))	2503.91 (1390.08)	<0.001
##	cnts (mean (SD))	1.00 (0.00)	<0.001
##	pairs (mean (SD))	1347.50 (777.84)	1.000



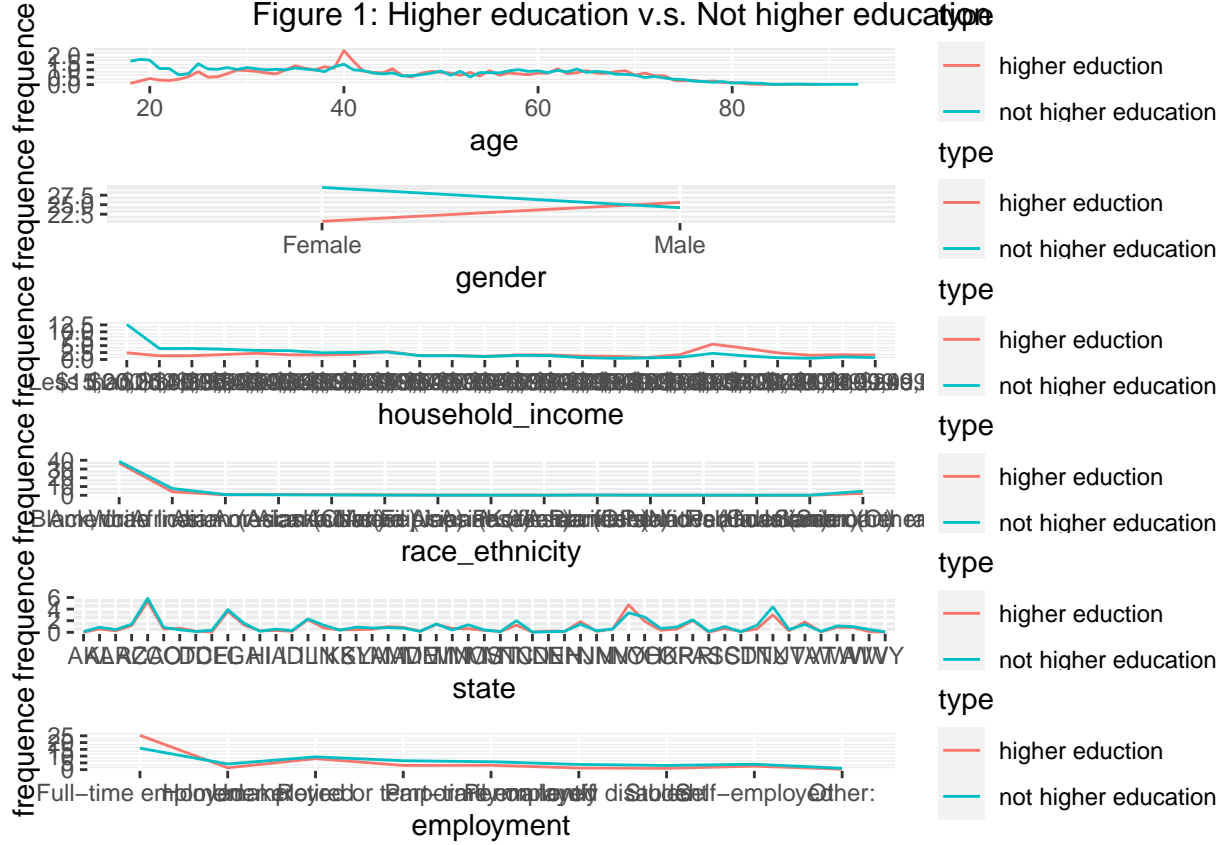


Table.1 reports the baseline characteristics of the data separated by treatment groups( higher education). In the table, the discrete variable, age, is summarized by means and standard deviations while categorical variables, such as gender and state, are summarized by frequency, The p-value printed along with the table is generated using hypothesis test: `chisq.test()` for categorical variables and `oneway.test()` for continuous variables, to compare the characteristics between two groups. From Table.1, it can be seen that the p-value of all variables in the table, except for `Vote_intention`, are smaller than 0.001, which is a threshold for statistical significance. Thus, these variables are good fits for explanatory variables of the regression model. From Figure.1, the differences in characteristics between the treatment group and the control group(higher education and not higher education) can also be seen more intuitively. It is shown that there are not so much differences between the two groups.

## Propensity Score matching

Propensity score matching is a statistical technique that matches treated and controlled group on the propensity score, which is the estimated probability of being treated. In this case, higher education is the treatment and the propensity score was calculated in the following logistic regression model:

$$\log\left(\frac{\hat{p}}{1-\hat{p}}\right) = \hat{\beta}_0 + \hat{\beta}_1 x_{age} + \hat{\beta}_2 x_{gender} + \hat{\beta}_3 x_{householdincome} + \hat{\beta}_4 x_{raceethnicity} + \hat{\beta}_5 x_{state}$$

where  $p$  represents the probability to have higher education.  $x_i(i=1\sim5)$  correspond to the values of age and the levels of gender, household income, state, and Race ethnicity. Age, gender, household income, state, and race\_ethnicity are the predictor variables.  $\beta_i(i=2\sim5)$  are estimate coefficients,  $\beta_0$  is an intercept. Then, for every person who was treated with higher education, we find the untreated person who was considered as the closest match based on the propensity score. After that, the dataset was reduced to just those that are matched. At last, the effect of being treated on Vote preference in the 2020 presidential election could be examined in the 'usual' way.

## Model:

The logistic regression model that we are interested in estimating is:

$$\log\left(\frac{\hat{p}}{1-\hat{p}}\right) = \hat{\beta}_0 + \hat{\beta}_1 x_{age} + \hat{\beta}_2 x_{gender} + \hat{\beta}_3 x_{householdincome} + \hat{\beta}_4 x_{raceethnicity} + \hat{\beta}_5 x_{state} + \hat{\beta}_6 x_{highereducation}$$

where  $p$  represents the probability to vote for Biden during 2020 presidential election.  $x_i$  ( $i=1\sim6$ ) correspond to the values of age and the levels of gender, household income, Race ethnicity, state, and higher education. Age, gender, household income, state, race\_ethnicity, and higher education are the predictor variables.  $\beta_i$  ( $i=2\sim6$ ) are estimate coefficients,  $\beta_0$  is an intercept.

## Results

	beta	
## (Intercept)	0.750753399	6.00e-01
## age	-0.013834024	2.96e-08
## genderMale	-0.439542068	2.81e-12
## household_income\$15,000 to \$19,999	0.067646076	6.93e-01
## household_income\$20,000 to \$24,999	-0.284649582	8.90e-02
## household_income\$25,000 to \$29,999	-0.156786394	3.39e-01
## household_income\$30,000 to \$34,999	-0.135065099	4.07e-01
## household_income\$35,000 to \$39,999	-0.143335374	4.04e-01
## household_income\$40,000 to \$44,999	-0.154051355	3.87e-01
## household_income\$45,000 to \$49,999	-0.255180409	1.38e-01
## household_income\$50,000 to \$54,999	-0.308245475	5.89e-02
## household_income\$55,000 to \$59,999	-0.337912990	9.40e-02
## household_income\$60,000 to \$64,999	-0.146131404	4.69e-01
## household_income\$65,000 to \$69,999	-0.222766901	3.11e-01
## household_income\$70,000 to \$74,999	-0.245152000	2.07e-01
## household_income\$75,000 to \$79,999	-0.420344224	3.09e-02
## household_income\$80,000 to \$84,999	-0.028225253	9.06e-01
## household_income\$85,000 to \$89,999	-0.201400962	4.26e-01
## household_income\$90,000 to \$94,999	-0.437018244	1.07e-01
## household_income\$95,000 to \$99,999	-0.122212250	5.63e-01
## household_income\$100,000 to \$124,999	-0.537573359	3.78e-04
## household_income\$125,000 to \$149,999	-0.496317602	2.73e-03
## household_income\$150,000 to \$174,999	-0.383102296	5.26e-02
## household_income\$175,000 to \$199,999	-0.912887111	9.00e-05
## household_income\$200,000 to \$249,999	-1.184968294	2.48e-08
## household_income\$250,000 and above	-0.792712117	3.35e-04
## employmentHomemaker	-0.170357662	2.69e-01
## employmentRetired	0.277658125	7.87e-03
## employmentUnemployed or temporarily on layoff	0.257697890	2.70e-02
## employmentPart-time employed	0.131213453	2.61e-01
## employmentPermanently disabled	0.361440656	2.30e-02
## employmentStudent	1.051764071	5.59e-06
## employmentSelf-employed	0.300091845	2.00e-02
## employmentOther:	0.350044846	2.29e-01
## stateAL	-0.126045211	9.31e-01
## stateAR	-0.218017838	8.82e-01
## stateAZ	0.154182777	9.15e-01
## stateCA	0.561416839	6.95e-01
## stateCO	0.248781495	8.64e-01
## stateCT	1.162094929	4.26e-01

## stateDC	0.348687150	8.19e-01
## stateDE	1.048140378	5.12e-01
## stateFL	0.130459848	9.27e-01
## stateGA	-0.248706561	8.63e-01
## stateHI	0.393106780	7.95e-01
## stateIA	0.514714307	7.25e-01
## stateID	0.001504026	9.99e-01
## stateIL	0.441285191	7.58e-01
## stateIN	0.265856972	8.54e-01
## stateKS	-0.278518359	8.49e-01
## stateKY	0.275204584	8.50e-01
## stateLA	-0.113969179	9.37e-01
## stateMA	1.150079653	4.27e-01
## stateMD	0.511423889	7.24e-01
## stateME	0.588425614	6.95e-01
## stateMI	0.454054996	7.52e-01
## stateMN	0.148842957	9.18e-01
## stateMO	0.251506288	8.62e-01
## stateMS	-0.265418747	8.57e-01
## stateMT	0.256774199	8.66e-01
## stateNC	0.088751349	9.51e-01
## stateND	-0.002088997	9.99e-01
## stateNE	0.546767370	7.17e-01
## stateNH	0.566117381	7.10e-01
## stateNJ	0.377708206	7.93e-01
## stateNM	0.858689293	5.71e-01
## stateNV	0.023643227	9.87e-01
## stateNY	0.438998273	7.59e-01
## stateOH	0.365128289	7.99e-01
## stateOK	0.127876624	9.30e-01
## stateOR	0.604110206	6.77e-01
## statePA	0.227508774	8.74e-01
## stateRI	1.894197129	2.92e-01
## stateSC	-0.368269580	7.99e-01
## stateSD	-0.027470259	9.86e-01
## stateTN	-0.116046770	9.36e-01
## stateTX	0.030849722	9.83e-01
## stateUT	0.642235134	6.62e-01
## stateVA	0.509463517	7.23e-01
## stateVT	2.439458380	1.68e-01
## stateWA	0.576352642	6.89e-01
## stateWI	0.677531238	6.39e-01
## stateWV	-0.344066848	8.17e-01
## stateWY	1.525386833	4.08e-01
## race_ethnicityBlack, or African American	2.071562782	3.58e-43
## race_ethnicityAmerican Indian or Alaska Native	-0.079677953	7.63e-01
## race_ethnicityAsian (Asian Indian)	0.419739966	1.13e-01
## race_ethnicityAsian (Chinese)	1.382496596	1.06e-04
## race_ethnicityAsian (Filipino)	-0.161147859	6.47e-01
## race_ethnicityAsian (Japanese)	0.798496030	1.98e-01
## race_ethnicityAsian (Korean)	0.429634124	4.92e-01
## race_ethnicityAsian (Vietnamese)	0.770852740	2.25e-01
## race_ethnicityAsian (Other)	0.756980817	1.15e-01
## race_ethnicityPacific Islander (Native Hawaiian)	0.601702855	5.12e-01

## race_ethnicityPacific Islander (Guamanian)	-12.556274519	9.69e-01
## race_ethnicityPacific Islander (Other)	12.147317660	9.40e-01
## race_ethnicitySome other race	0.763548833	5.98e-08
## edu_high1	0.267783655	4.24e-05

The Propensity score regression is based on age, gender, household income, employment, state, race\_ethnicity, and higher education and it looks for the proportion of voters who are more willing to vote for Biden.

The results of the model show that age, gender, household income, employment, race\_ethnicity, and higher education are significant predictors of voters' preferences because their p-value is less than 0.05. Moreover, age, gender, and higher education are especially significant in influencing voters' preferences because their p-value is less than 0.001.

The propensity score adjusted data can be used to assess the causality of treatment (higher education). It can be seen from the table that the coefficient of edu\_high is 0.268. This means that for the person with higher education, the log odds of the percentage of voters who are more willing to vote for Biden will increase by 0.268.

## Discussion

### Summary

The Democracy Foundation + UCLA Nationscape survey data (2020) was used to analyze the effects of higher education on voters' preferences for candidates of the U.S. Presidential election 2020. Firstly, a few variables were selected from the original dataset. Then, the dataset was adjusted by propensity score matching while the treatment is higher education. Finally, a propensity score regression was conducted to draw causal inferences about the treatment.

### Conclusions

The results of the propensity score regression indicated that the treatment of higher education is statistically significant. It also assessed the causality of treatment, that is, highly educated voters are more likely to choose Biden as the next president of the United States. The results show that for those with higher education, the log odds of the proportion of voters who are more willing to vote for Biden will increase by 0.268.

People with higher education may have realized the benefits brought by higher education. They may vote for the one that will formulate the policies that benefit education. Therefore, inferences about the causal relationship between higher education and voting preferences can provide references to government agencies in advancing a comprehensive higher education agenda. Also, today, higher education is an important contribution to the country's competitiveness in the global market and is vital to economic strength, social well-being, and world leadership. In other words, the development of high education is closely related to the future of society. Hence, it is necessary for the government to pay more attention to higher education.

### Weakness & Next Steps:

There are some flaws in propensity score matching. One of them is modeling. The basic assumption for using propensity scores is that all confounders of treatment options and outcomes have been measured and included in the propensity model. The results tend to be specific to the model that is used. If the model does not include variables strongly related to both outcome and assignment, it may increase bias. From the results of the final model, it is seen that the variable of state is not statistically significant. Thus, this possibly increases bias. Also, there may be bias due to confounding factors that cannot be measured. However, if propensity scores are constructed based only on treatment covariates that are statistically significantly different between the pre-treatment and comparison groups, they will not be able to consider the relationships between the covariates and the results.

Therefore, for the next step, our goal should be creating as rich a propensity score model as possible while including a strong covariate.

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