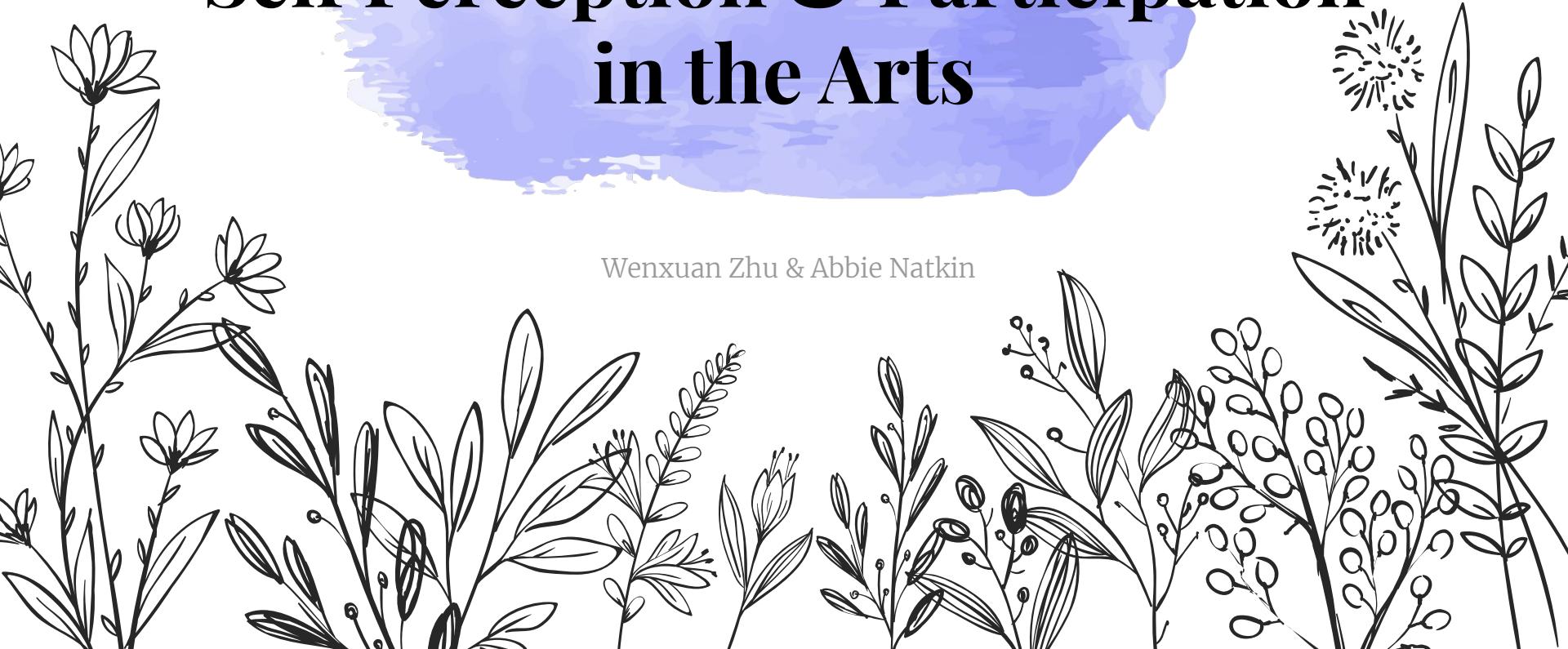


# Self Perception & Participation in the Arts

Wenxuan Zhu & Abbie Natkin

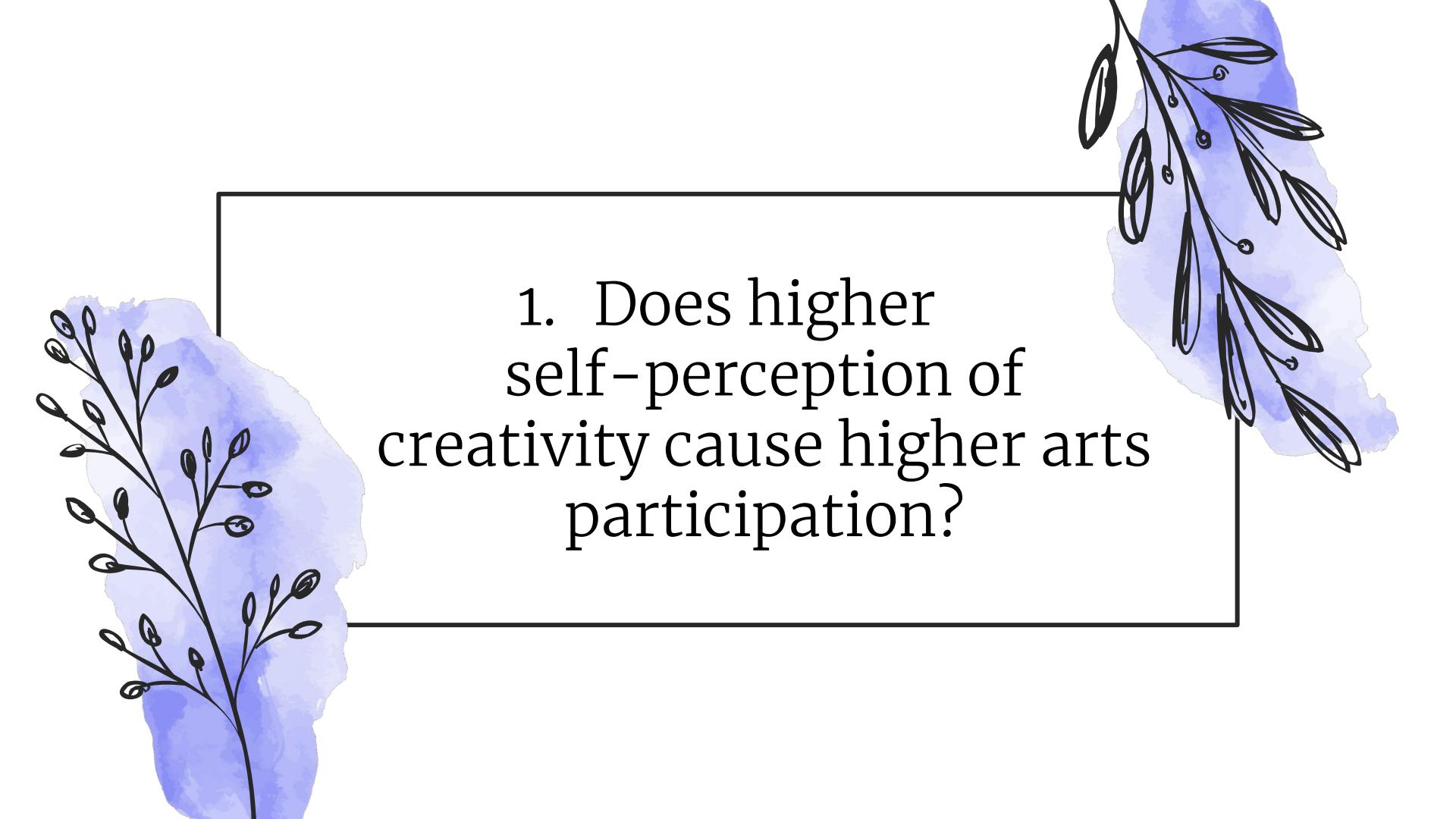




**01**  
Data

**02**  
Regression  
Analysis & IPW

**03**  
Sensitivity  
Analysis



1. Does higher self-perception of creativity cause higher arts participation?



O1

Data!

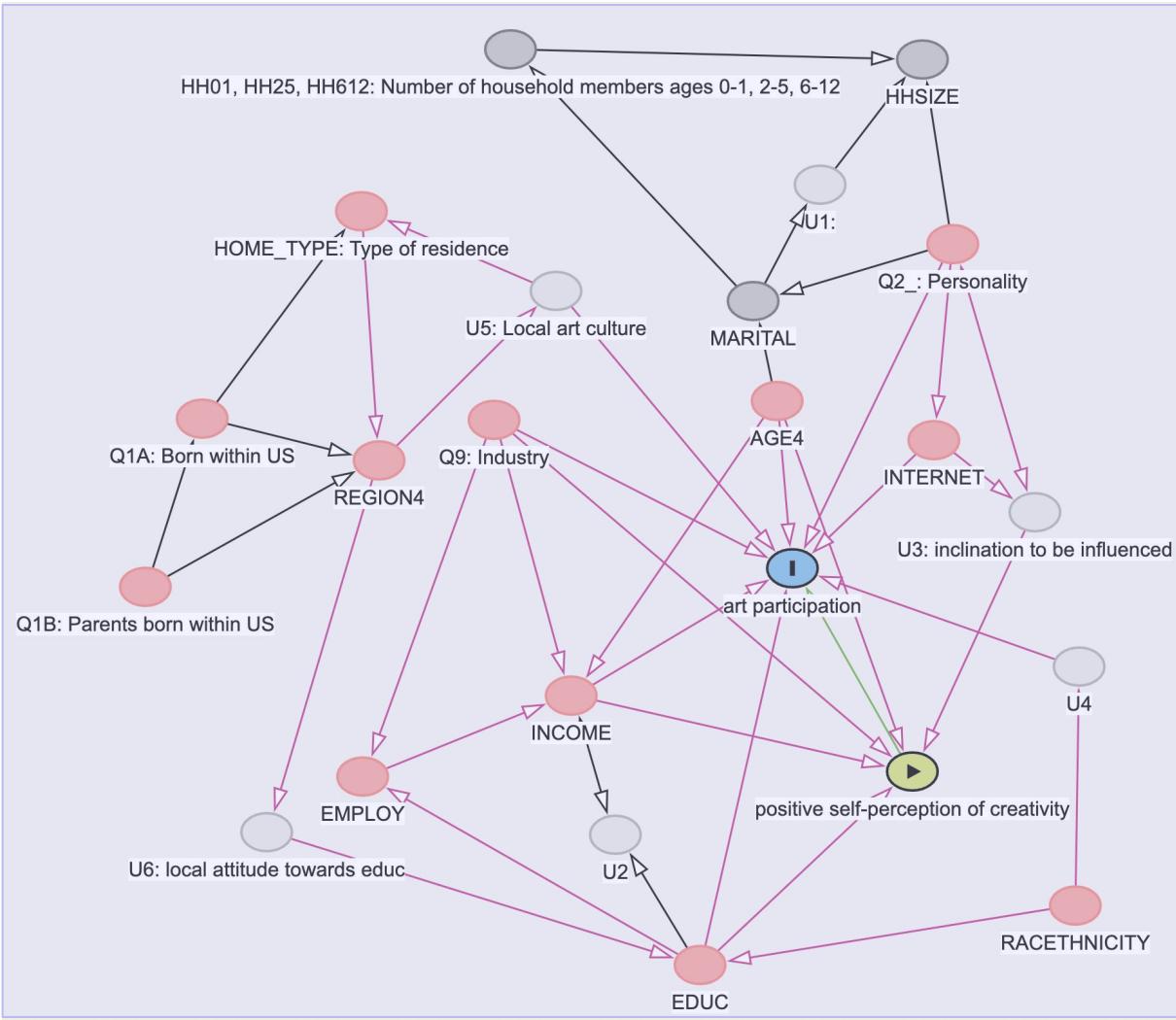
# Data Overview



## “Self perceptions of Creativity & Arts Participation,” 2018

- ★ Survey given to 3,447 adults in the US of differing demographics and socioeconomic status
- ★ “The primary objective of the national survey is to measure the ways that American adults experience and exercise creativity in their daily lives.”
- ★ “...self-perceptions of creativity across six creative "domains": artistic creativity, creativity in math/science, creativity in business/entrepreneurship, creativity in social settings, creativity in civic settings, and creativity in "everyday" activities”

# DAG





# Important Variables

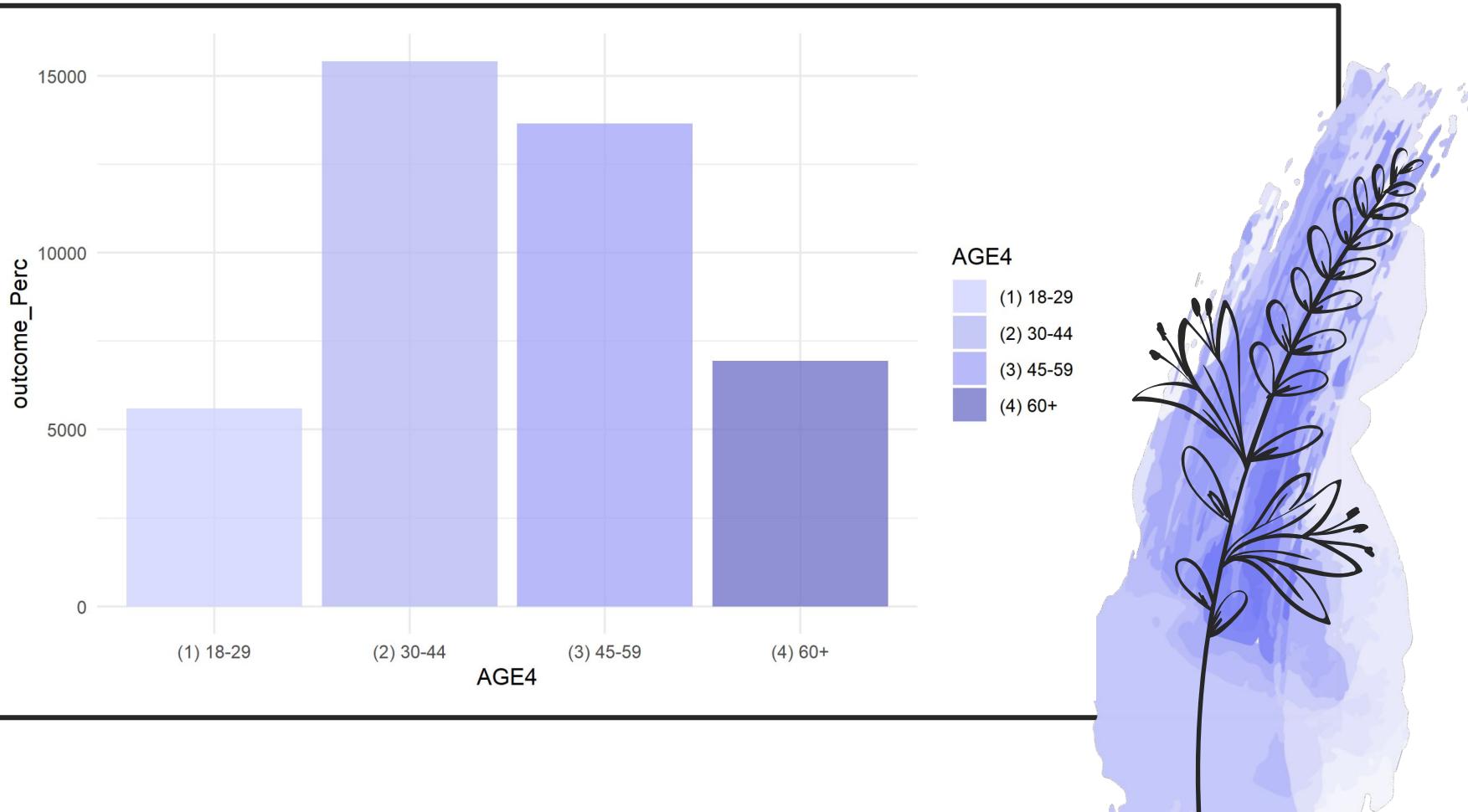
- ★ Outcome variable:
  - ie. During the last 12 months did you go to a musical, play an instrument, go to an art exhibit, etc.
  
- ★ Treatment
  - ie. Compared to people of approximately your age and life experience, how relatively creative are you in making up lyrics to a song, making up dance moves, solving puzzles, etc.



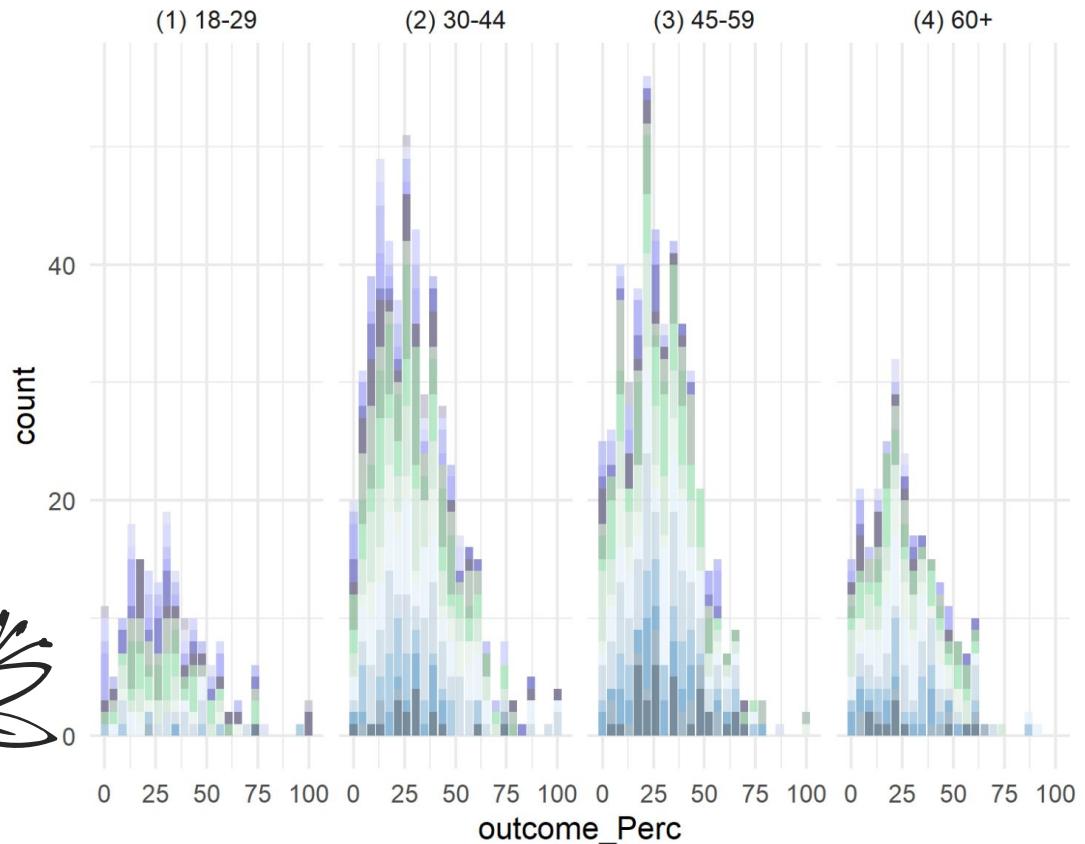
# Minimal Sufficient Condition

Minimal sufficient adjustment sets:

- AGE4
- EDUC
- INCOME
- INTERNET
- Personality\_Perc

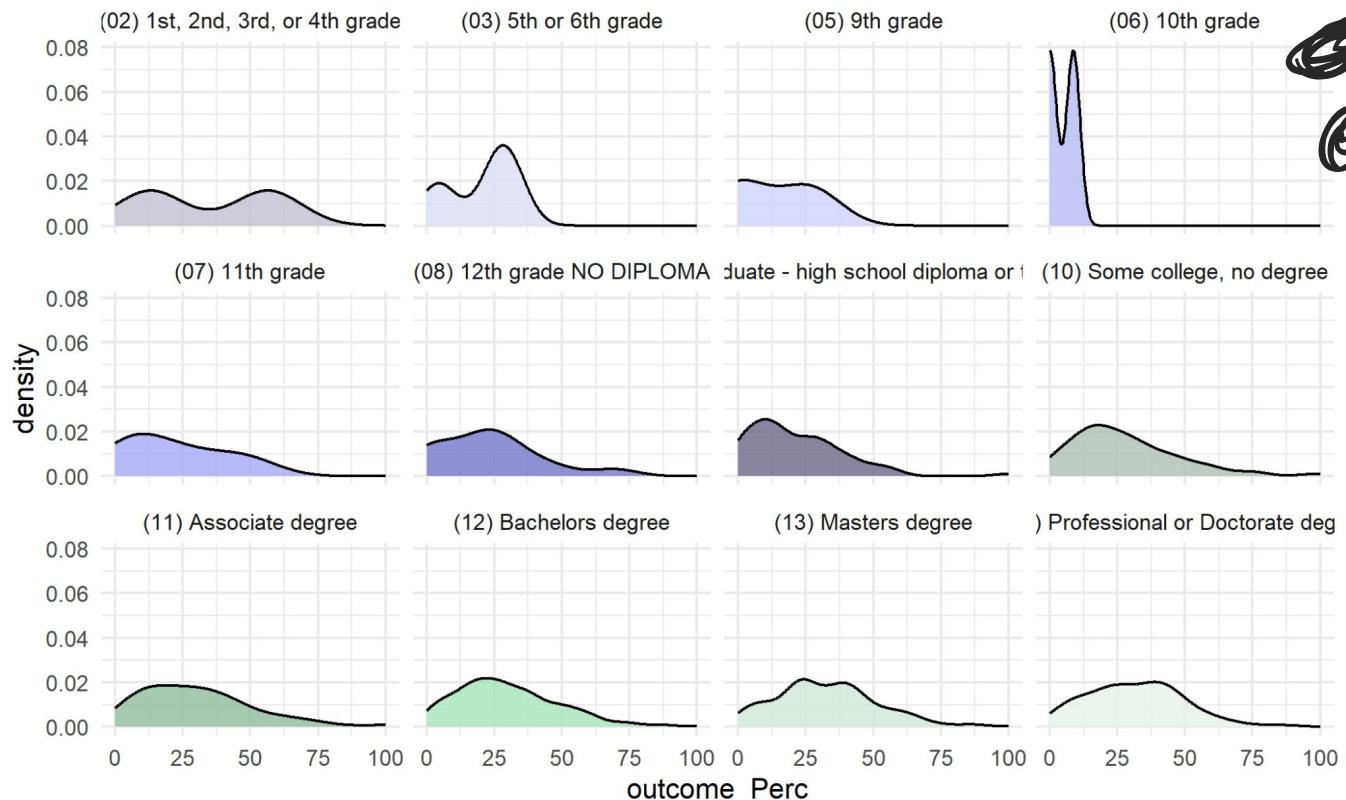


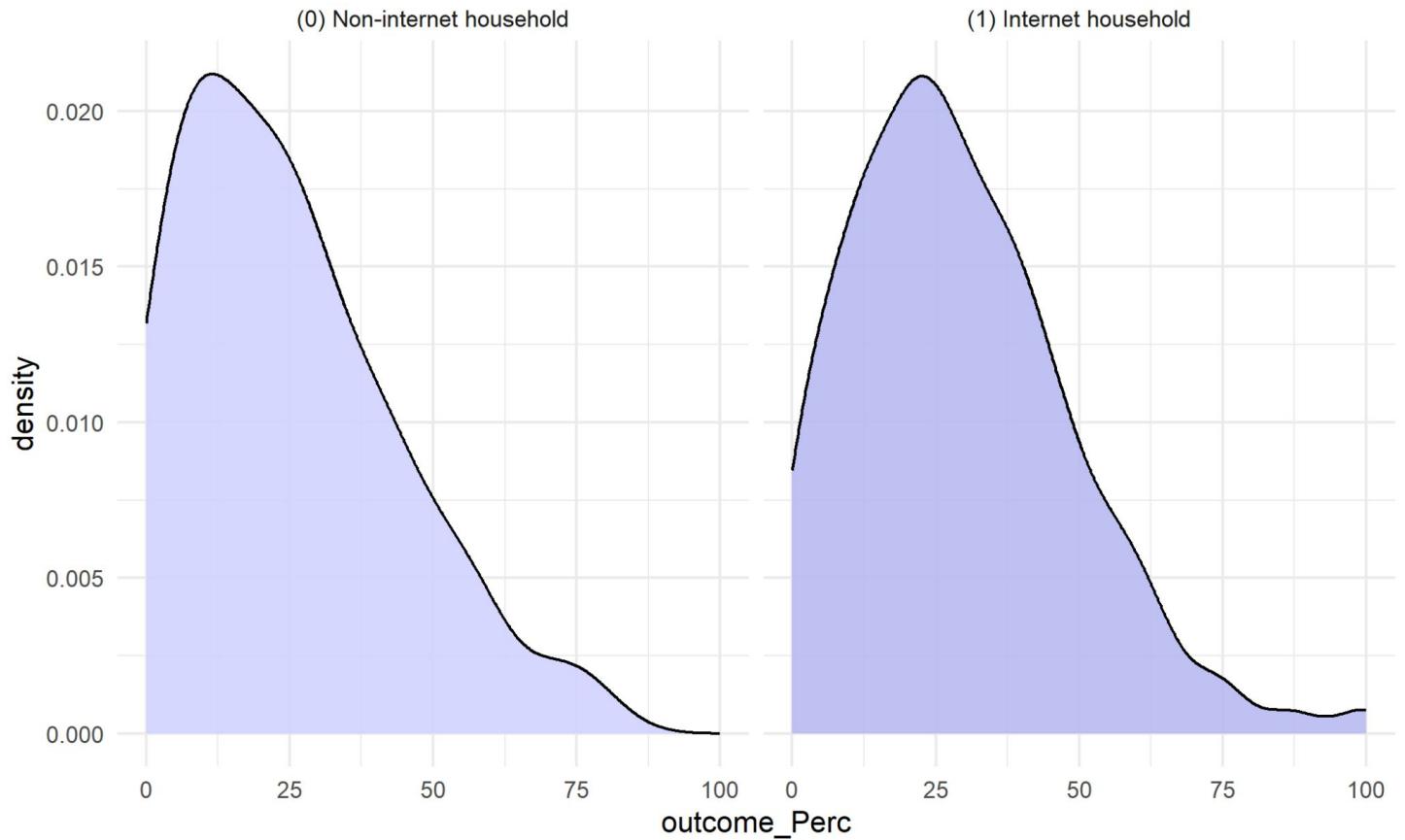
## Outcome\_Perc by Income categorized by 4 Age group



factor(INCOME)

- (01) Less than \$5,000
- (02) \$5,000 to \$9,999
- (03) \$10,000 to \$14,999
- (04) \$15,000 to \$19,999
- (05) \$20,000 to \$24,999
- (06) \$25,000 to \$29,999
- (07) \$30,000 to \$34,999
- (08) \$35,000 to \$39,999
- (09) \$40,000 to \$49,999
- (10) \$50,000 to \$59,999
- (11) \$60,000 to \$74,999
- (12) \$75,000 to \$84,999
- (13) \$85,000 to \$99,999
- (14) \$100,000 to \$124,999
- (15) \$125,000 to \$149,999
- (16) \$150,000 to \$174,999
- (17) \$175,000 to \$199,999
- (18) \$200,000 or more





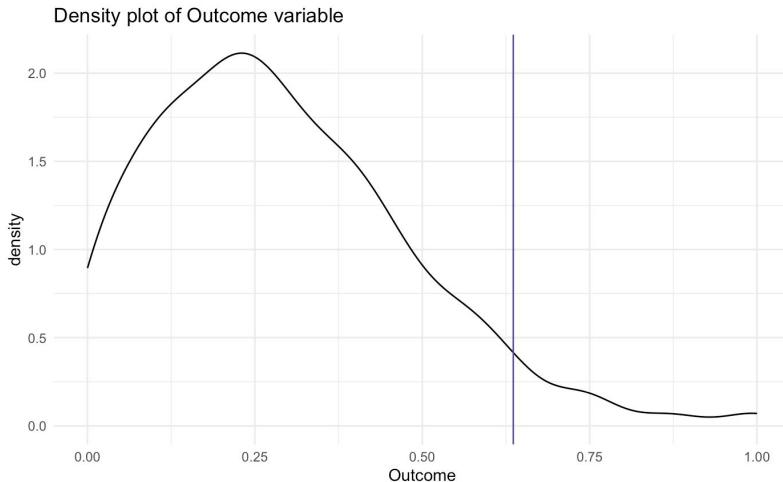
A decorative illustration of white line-art floral branches and leaves, including small flowers and larger, more detailed leafy sprigs, arranged in a flowing, organic pattern across the top half of the slide.

02

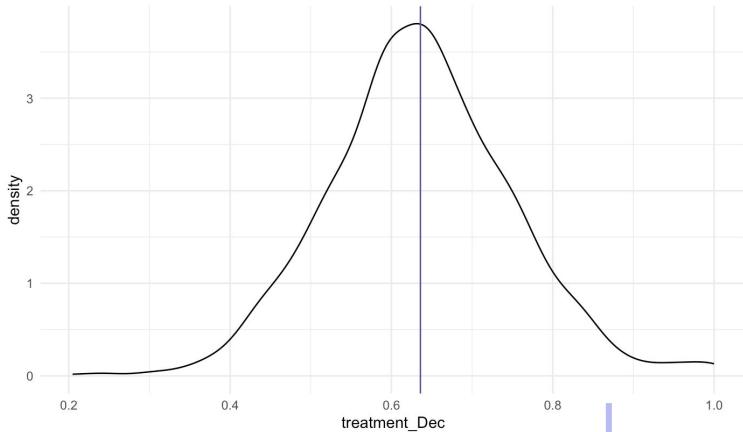
Regression Analysis!

# Data Manipulation

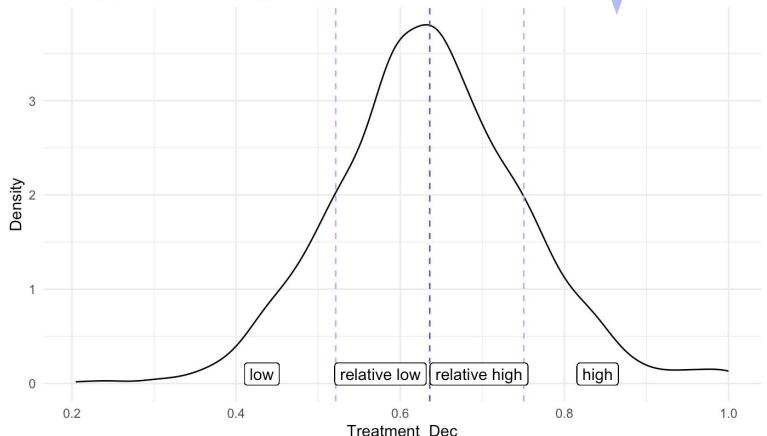
- Treatment variable → 4 categories
- Outcome variable → binary
- Income → 3 categories



Density plot of Treatment\_Dec



Density plot of Treatment\_Dec



# Outcome Regression



Goal:

- Condition on confounding variables to disable non-causal paths

Model Code:

- mod\_overall <- glm(Outcome ~ treatment\_Dec + AGE4 + EDUC + income\_3 + ns(personality\_Perc, 2) + INTERNET + Q9, family = "binomial", data = df)

- summary(mod\_overall)

```
## Call:  
## glm(formula = Outcome ~ treatment_Dec + AGE4 + EDUC + income_3 +  
##       ns(personality_Perc, 2) + INTERNET + Q9, family = "binomial",  
##       data = df)  
  
## Deviance Residuals:  
##      Min        1Q     Median        3Q       Max  
## -1.52401  -0.27665  -0.01838   0.20438   1.84755  
  
##  
## Coefficients:  
##  
##             Estimate  
## (Intercept) -3.028368  
## treatment_Dec 3.634765  
## AGE4(2) 30-44 -0.120705  
## AGE4(3) 45-59 -0.200314  
## AGE4(4) 60+   -0.299955  
## EDUC(03) 5th or 6th grade -0.590374  
## ...  
##
```

Output →

# Average Causal Effect Estimates



```
## # A tibble: 1 × 8
##   term      estimate std.error statistic p.value odds_ratio ci_lower ci_upper
##   <chr>     <dbl>     <dbl>     <dbl>    <dbl>     <dbl>     <dbl>     <dbl>
## 1 treatment_...  3.63     0.559     6.50 7.77e-11     37.9     12.7    113.
```

→ A strong positive causal relationship!

# IPW Analysis



## Random Forest:

- Recipe: `data_rec <- recipe(treatment_Cat4_Change ~ AGE4 + EDUC + income_3 + personality_Perc + INTERNET + Q9, data = df_rf)`

```
## └ Workflow [trained] ──────────────────────────────────────────────────────────  
## Preprocessor: Recipe  
## Model: rand_forest()  
##  
## └ Preprocessor ──────────────────────────────────────────────────────────  
## 0 Recipe Steps  
##  
## └ Model ──────────────────────────────────────────────────────────────────  
##  Ranger result  
##  
## Call:  
##   ranger::ranger(x = maybe_data_frame(x), y = y, mtry = min_cols(~6,      x), num.trees = ~1000, min.node.size  
= min_rows(~2, x), probability = ~TRUE,      importance = ~"impurity", num.threads = 1, verbose = FALSE,      see  
d = sample.int(10^5, 1))  
##  
## Type:                      Probability estimation  
## Number of trees:           1000  
## Sample size:                1444  
## Number of independent variables: 6  
## Mtry:                      6  
## Target node size:          2  
## Variable importance mode:  impurity  
## Splitrule:                 gini  
## OOB prediction error (Brier s.): 0.5453149
```

Optimal workflow (`mtry` = 6) →

# IPW Analysis Weighting



Code:

- rf6\_predict <- as.data.frame(predict(data\_fit\_mtry6, new\_data = df, type = "prob"))
- df\_rf <- cbind(df, rf6\_predict)
- df <- df\_rf %>%
  - mutate(ps = case\_when(treatment\_Cat4\_num == 0 ~ .pred\_low,  
treatment\_Cat4\_num == 0.25 ~ `pred\_relative low`,  
treatment\_Cat4\_num == 0.75 ~ `pred\_relative high`,  
treatment\_Cat4\_num == 1 ~ .pred\_high),
- ipw = 1/ps)

# IPW Analysis Result



```
## Call:  
## svyglm(formula = outcome_Cat2 ~ as.factor(treatment_Cat4_num),  
##          design = design, family = "quasibinomial", data = df_subs)  
##  
## Survey design:  
## svydesign(ids = ~0, weights = df_subs$ipw, data = df_subs)  
##  
## Coefficients:  
##  
##             Estimate Std. Error t value Pr(>|t|)  
## (Intercept) -1.6902    0.2034 -8.310 < 2e-16 ***  
## as.factor(treatment_Cat4_num)0.25  1.1288    0.2248  5.022 5.75e-07 ***  
## as.factor(treatment_Cat4_num)0.75  2.0443    0.2241  9.124 < 2e-16 ***  
## as.factor(treatment_Cat4_num)1    2.6553    0.2596 10.227 < 2e-16 ***  
## ---  
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1  
##  
## (Dispersion parameter for quasibinomial family taken to be 1.000693)  
##  
## Number of Fisher Scoring iterations: 4
```

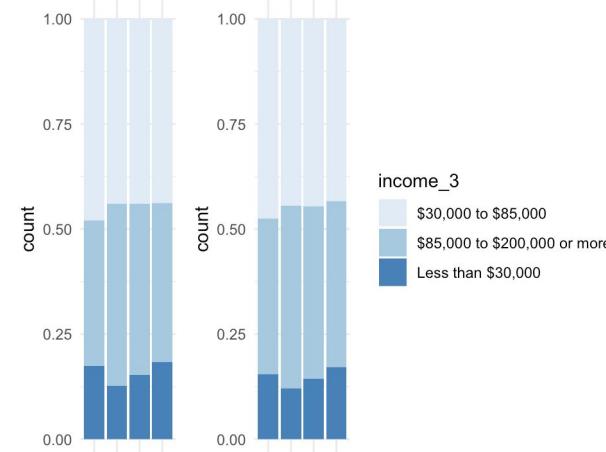
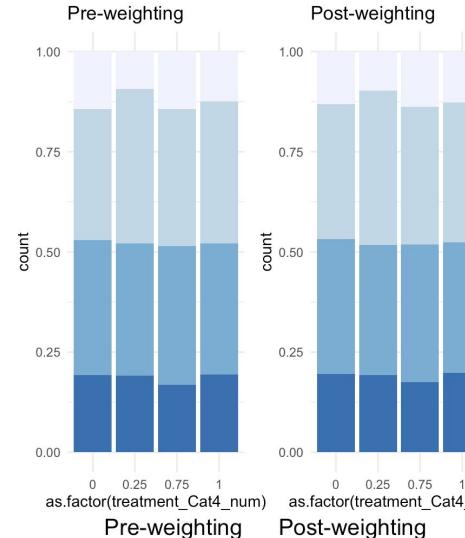
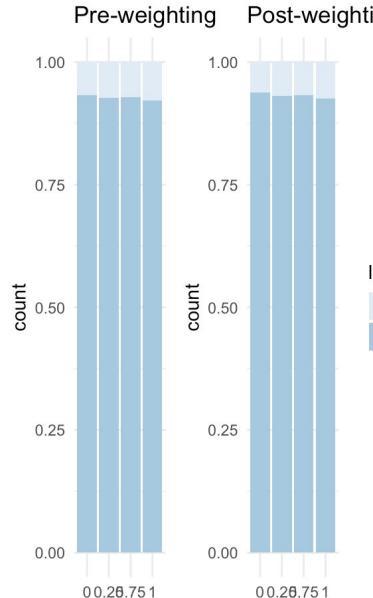
	2.5 %	97.5 %
## (Intercept)	-2.0892093	-1.291263
## as.factor(treatment_Cat4_num)0.25	0.6878818	1.569714
## as.factor(treatment_Cat4_num)0.75	1.6047517	2.483801
## as.factor(treatment_Cat4_num)1	2.1459538	3.164554



→ Consistent with outcome regression model

# Balance Checking

- Nuanced differences between pre & post-weighting



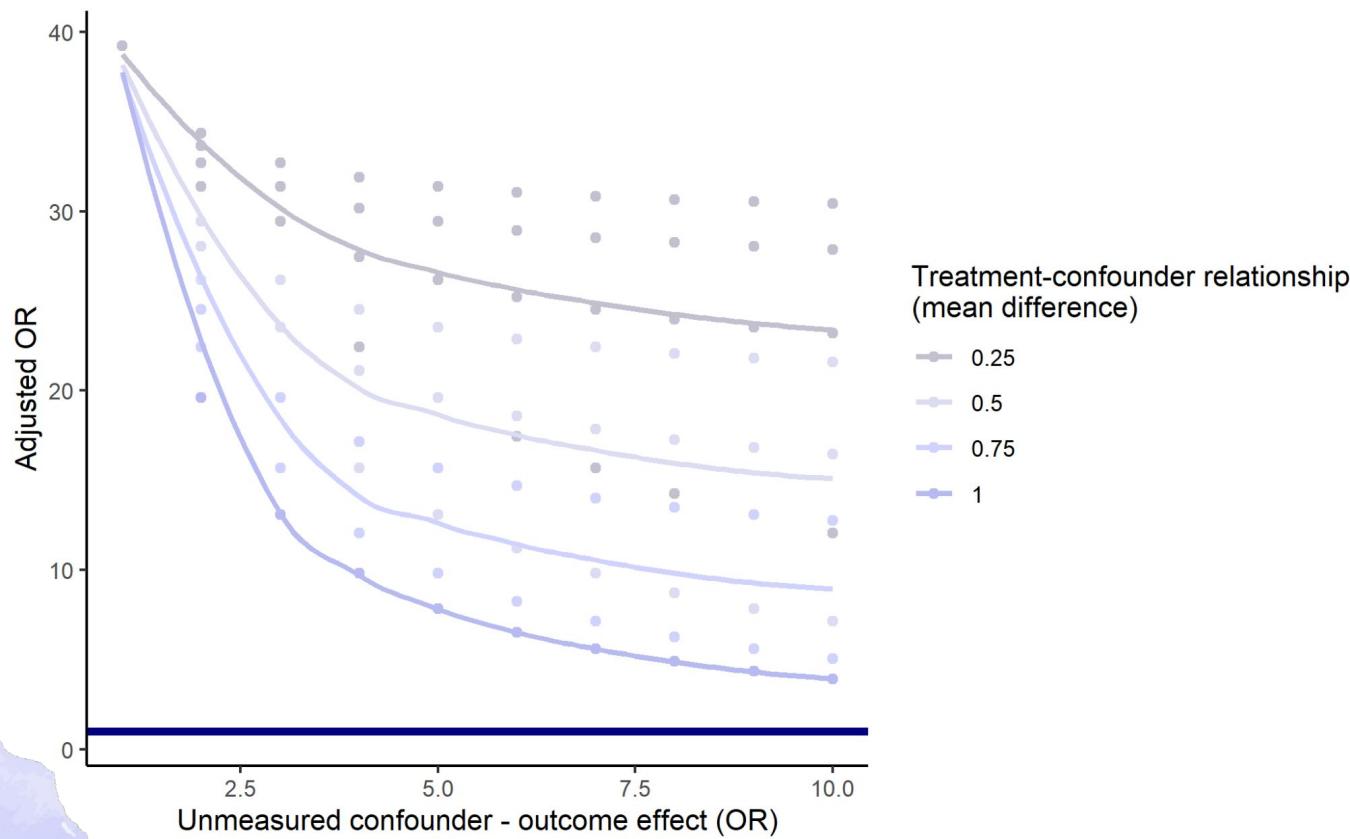
Statistical weights for the study eligible respondents were calculated using panel base sampling weights to start.



03

Sensitivity Analysis!

# Sensitivity Analysis





2. Does a positive self-perception cause higher arts participation?

## New Treatment Variable (Perception of Positive Personality Traits)

- ★ Thorough
- ★ Helpful
- ★ Energy
- ★ Clever
- ★ Enthusiastic
- ★ Trusting
- ★ Confident
- ★ Kind
- ★ Outgoing



```
mod_PP <- glm(Outcome ~ secondPositivePersonality_Perc + AGE4 + EDUC + income_3 +  
ns(personality_Perc, 2) + INTERNET + Q9, family = "binomial", data = df)
```

	(Intercept)	secondPositivePersonality_perc
-1.48401940		0.01758004

[1] 0.02422978

Odds Ratio = 1.0177

# Thanks!

