

# Causal Modeling With GSS Data Using Multiple Approaches

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## Research Question

What is the *possibly causal* association of *education* with *job satisfaction*, while accounting for factors that may possibly have an association with *level of education*?

## Causality

A variable  $x$  can only be considered to have *causal* association with  $y$  if the following conditions are met (Holland, 1986):

1.  $x$  is correlated with  $y$ .
2.  $x$  precedes  $y$  in time order.
3. The association between  $x$  and  $y$  can not be accounted for by any third variable  $z$ .

Hence, for this particular data, we are exploring:

What happens to the association of *education* and *job satisfaction* when we control for possible confounding variables  $z$  using various statistical strategies?

## To Be Added To Each Analysis

- Assumptions
- Equation
- Stata Command
- Conclusion

## Setup

```
. clear all

. cd "/Users/agrogan/Desktop/newstuff/causal-modeling"
/Users/agrogan/Desktop/newstuff/causal-modeling
```

## Get Data

```
. use "/Users/agrogan/Box Sync/DATA WAREHOUSE/General Social Survey Panel Data/GSS_panel2
> 010w123_R6 - stata.dta", clear
```

## ID Variable

```
. generate ID = id_1
```

## Keep Only Relevant Variables

```
. keep ID satjob_? educ_? race_? incom16_?
```

## Describe Data

```
. describe
Contains data from /Users/agrogon/Box Sync/DATA WAREHOUSE/General Social Survey Panel Dat
> a/GSS_panel2010w123_R6 - stata.dta
obs:          2,044
vars:           13          5 Jul 2020 13:27
size:         32,704
```

variable name	storage type	display format	value label	variable label
educ_1	byte	%8.0g	EDUC_1	educ_1: HIGHEST YEAR OF SCHOOL COMPLETED
educ_2	byte	%8.0g	EDUC_2	educ_2: HIGHEST YEAR OF SCHOOL COMPLETED
educ_3	byte	%8.0g	EDUC_3	educ_3: HIGHEST YEAR OF SCHOOL COMPLETED
incom16_1	byte	%8.0g	INCOM16	incom16_1: RS FAMILY INCOME WHEN 16 YRS OLD
incom16_2	byte	%8.0g	V1318_A	incom16_2: RS FAMILY INCOME WHEN 16 YRS OLD
incom16_3	byte	%8.0g	V1319_A	incom16_3: RS FAMILY INCOME WHEN 16 YRS OLD
race_1	byte	%8.0g	RACE_1	race_1: RACE OF RESPONDENT
race_2	byte	%8.0g	RACE_2	race_2: RACE OF RESPONDENT
race_3	byte	%8.0g	RACE_3	race_3: RACE OF RESPONDENT
satjob_1	byte	%8.0g	SATJOB_1	satjob_1: JOB OR HOUSEWORK
satjob_2	byte	%8.0g	SATJOB_2	satjob_2: JOB OR HOUSEWORK
satjob_3	byte	%8.0g	SATJOB_3	satjob_3: JOB OR HOUSEWORK
ID	float	%9.0g		

Sorted by:

Note: Dataset has changed since last saved.

## Codebook For Selected Variable(s)

```
. codebook satjob_3
```

satjob_3		satjob_3: JOB OR HOUSEWORK	
type: numeric (byte)			
label: SATJOB_3			
range: [1,4]		units: 1	
unique values: 4		missing .: 0/2,044	
unique mv codes: 3		missing .*: 1,086/2,044	
tabulation:	Freq.	Numeric	Label
	483	1	VERY SATISFIED
	367	2	MOD. SATISFIED
	69	3	A LITTLE DISSAT
	39	4	VERY DISSATISFIED
	4	.d	DK
	1,073	.i	IAP
	9	.n	NA

# Analyses Relying On Wide Data

## Correlation

```
. pwcorr satjob_3 educ_3, sig
```

	satjob_3	educ_3
satjob_3	1.0000	
educ_3	-0.0774 0.0166	1.0000

## Regression With 1 Independent Variable

```
. regress satjob_3 educ_3
```

Source	SS	df	MS	Number of obs	=	957
Model	3.53828635	1	3.53828635	F(1, 955)	=	5.76
Residual	586.493062	955	.61412886	Prob > F	=	0.0166
				R-squared	=	0.0060
				Adj R-squared	=	0.0050
Total	590.031348	956	.617187602	Root MSE	=	.78366

satjob_3	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
educ_3	-.0216864	.0090349	-2.40	0.017	-.0394169	-.003956
_cons	1.954439	.1297867	15.06	0.000	1.699739	2.209139

## Regression With Multiple Independent Variables

```
. regress satjob_3 educ_3 i.race_3 incom16_3
```

Source	SS	df	MS	Number of obs	=	951
Model	5.81703392	4	1.45425848	F(4, 946)	=	2.36
Residual	582.580442	946	.615835563	Prob > F	=	0.0517
				R-squared	=	0.0099
				Adj R-squared	=	0.0057
Total	588.397476	950	.619365765	Root MSE	=	.78475

satjob_3	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
educ_3	-.0215151	.0092674	-2.32	0.020	-.0397021	-.0033281
race_3						
black	.1267666	.0708898	1.79	0.074	-.0123528	.2658861
other	.0677238	.0985112	0.69	0.492	-.1256019	.2610495
incom16_3	.0115275	.0280601	0.41	0.681	-.0435398	.0665947
_cons	1.89556	.144649	13.10	0.000	1.61169	2.17943

## Propensity Score

### Data Wrangling Since Propensity Score Requires a Binary Treatment Variable

```
. generate twelve_years_3 = educ_3 >= 12 // 12 or more years of education
. generate twelve_years_2 = educ_2 >= 12 // 12 or more years of education
```

```
. generate twelve_years_1 = educ_1 >= 12 // 12 or more years of education

. label variable twelve_years_3 "12 or more years of education"

. label variable twelve_years_2 "12 or more years of education"

. label variable twelve_years_1 "12 or more years of education"
```

## Propensity Score Analysis

```
. teffects psmatch (satjob_3) (twelve_years_3 incom16_3 i.race_3)
Treatment-effects estimation      Number of obs      =      952
Estimator      : propensity-score matching      Matches: requested =      1
Outcome model  : matching                      min =      1
Treatment model: logit                      max =     296
```

	satjob_3	Coef.	AI Robust Std. Err.	z	P> z	[95% Conf. Interval]
ATE						
twelve_years_3 (1 vs 0)		-.0410168	.1083808	-0.38	0.705	-.2534393 .1714057

## Assess Balance of Propensity Score Model <sup>1</sup>

```
. tebalance summarize
note: refitting the model using the generate() option
Covariate balance summary
```

	Raw	Matched
Number of obs =	952	1,904
Treated obs =	854	952
Control obs =	98	952

	Standardized differences		Variance ratio	
	Raw	Matched	Raw	Matched
incom16_3	.5429864	-.0077616	.9418824	.9726307
race_3				
black	-.1354119	-.0199848	.7873145	.9638265
other	-.0248378	.0326166	.9163586	1.114865

```
. tebalance density, scheme(michigan)
note: refitting the model using the generate() option

. graph export mydensity.png, width(500) replace
(file mydensity.png written in PNG format)
```

## Analyses Relying On Long Data

### Reshape The Data

```
. reshape long satjob_ educ_ twelve_years_ incom16_ race_, i(ID) j(wave)
(note: j = 1 2 3)
```

<sup>1</sup>With many thanks to Jorge Cuartas for the ideas for earlier versions of this code.

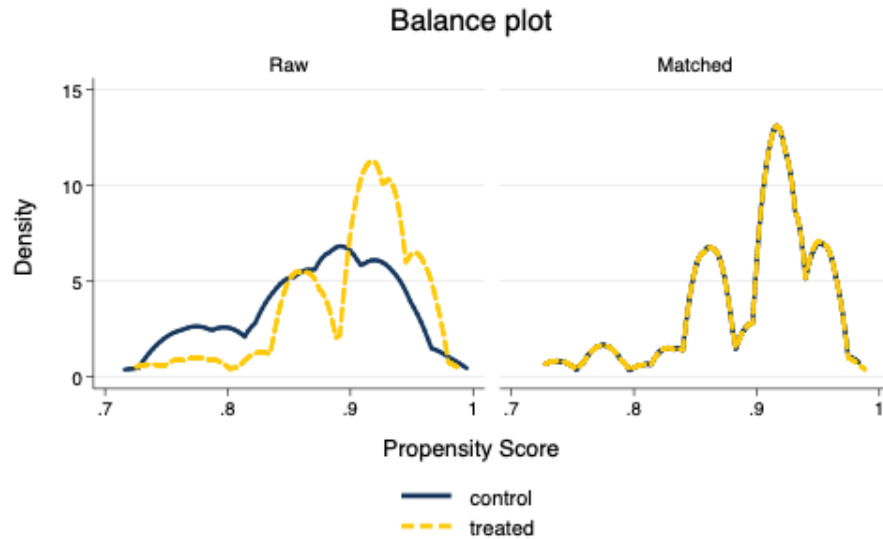


Figure 1: Density Plot of Propensity Score

Data	wide	->	long
Number of obs.	2044	->	6132
Number of variables	16	->	7
j variable (3 values)		->	wave
xij variables:			
satjob_1 satjob_2 satjob_3		->	satjob_
educ_1 educ_2 educ_3		->	educ_
twelve_years_1 twelve_years_2 twelve_years_3		->	twelve_years_
incom16_1 incom16_2 incom16_3		->	incom16_
race_1 race_2 race_3		->	race_

## Clean Up Variable Names

```
. rename satjob_ satjob
. rename educ_ educ
. rename incom16_ incom16
. rename race_ race
. rename twelve_years_ twelve_years
```

## Multilevel Model

```
. mixed satjob wave educ incom16 i.race || ID:
Performing EM optimization:
Performing gradient-based optimization:
Iteration 0:  log likelihood = -4161.775
Iteration 1:  log likelihood = -4161.7476
Iteration 2:  log likelihood = -4161.7476
Computing standard errors:
```

Mixed-effects ML regression  
Group variable: ID

Number of obs = 3,595  
Number of groups = 1,661  
Obs per group:  
min = 1  
avg = 2.2  
max = 3

Log likelihood = -4161.7476

Wald chi2(5) = 42.38  
Prob > chi2 = 0.0000

satjob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
wave	-.018625	.014015	-1.33	0.184	-.0460938	.0088439
educ	-.018976	.0054133	-3.51	0.000	-.0295859	-.008366
incom16	-.0350535	.0154559	-2.27	0.023	-.0653465	-.0047606
race						
black	.1695589	.0451171	3.76	0.000	.0811311	.2579868
other	.035975	.0543135	0.66	0.508	-.0704776	.1424276
_cons	2.049073	.0843019	24.31	0.000	1.883845	2.214302

Random-effects Parameters		Estimate	Std. Err.	[95% Conf. Interval]	
ID: Identity	var(_cons)	.2305185	.0161162	.2009999	.2643722
	var(Residual)	.4174209	.0131143	.3924927	.4439323

LR test vs. linear model: chibar2(01) = 322.95      Prob >= chibar2 = 0.0000

## Fixed effects regression

. xtreg satjob wave educ incom16 i.race, i(ID) fe  
Fixed-effects (within) regression  
Group variable: ID

R-sq:  
within = 0.0052  
between = 0.0148  
overall = 0.0122

Number of obs = 3,595  
Number of groups = 1,661  
Obs per group:  
min = 1  
avg = 2.2  
max = 3

F(5,1929) = 2.03  
Prob > F = 0.0711

corr(u\_i, Xb) = -0.0714

satjob	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
wave	-.0237842	.0152551	-1.56	0.119	-.0537023	.006134
educ	-.0087664	.0158008	-0.55	0.579	-.0397548	.022222
incom16	-.047186	.0228265	-2.07	0.039	-.0919531	-.0024189
race						
black	.3226033	.2025604	1.59	0.111	-.0746572	.7198637
other	.0383663	.104807	0.37	0.714	-.1671806	.2439132
_cons	1.928458	.227991	8.46	0.000	1.481323	2.375593
sigma_u	.6861769					
sigma_e	.64822634					
rho	.52841711	(fraction of variance due to u_i)				

F test that all u\_i=0: F(1660, 1929) = 2.18      Prob > F = 0.0000

## “Hybrid” Model

The contention here is that the *between person* coefficient replicates the effect of the fixed effects regression coefficient while the *within person* coefficient is simultaneously estimated.

### Generate Within And Between Variables

```
. bysort ID: egen educ_mean = mean(educ)
(6 missing values generated)

. generate educ_deviation = educ - educ_mean
(1,240 missing values generated)
```

### Estimate The Model

```
. mixed satjob wave educ_mean educ_deviation incom16 i.race || ID:
Performing EM optimization:
Performing gradient-based optimization:
Iteration 0:   log likelihood = -4161.3224
Iteration 1:   log likelihood = -4161.2951
Iteration 2:   log likelihood = -4161.2951
Computing standard errors:
Mixed-effects ML regression              Number of obs   =       3,595
Group variable: ID                      Number of groups =       1,661
                                         Obs per group:
                                         min =           1
                                         avg =           2.2
                                         max =           3
                                         Wald chi2(6)     =       43.30
                                         Prob > chi2      =       0.0000
Log likelihood = -4161.2951
```

satjob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
wave	-.0197009	.0140588	-1.40	0.161	-.0472556	.0078537
educ_mean	-.0208983	.0057775	-3.62	0.000	-.0322221	-.0095745
educ_deviation	-.0054971	.0151667	-0.36	0.717	-.0352233	.0242292
incom16	-.0343579	.0154712	-2.22	0.026	-.0646809	-.0040349
race						
black	.1684699	.0451261	3.73	0.000	.0800245	.2569154
other	.0342568	.0543368	0.63	0.528	-.0722414	.140755
_cons	2.075849	.088866	23.36	0.000	1.901675	2.250023

Random-effects Parameters		Estimate	Std. Err.	[95% Conf. Interval]	
ID: Identity					
	var(_cons)	.2304651	.0161097	.2009581	.2643046
	var(Residual)	.4173132	.0131099	.3923934	.4438157

LR test vs. linear model: chibar2(01) = 323.08      Prob >= chibar2 = 0.0000

## Difference In Difference Model

### References

Holland, P. W. (1986). Statistics and Causal Inference. *Journal of the American Statistical Association*, 81(396), 945–960. <https://doi.org/10.1080/01621459.1986.10478354>