Example Populated Preanalyis Plan*

2023-01-25

This document offers an example populated preanalysis plan (populated PAP, Banerjee et al. (2020)). In a populated PAP, the pre-registered analyses are performed without modification. Populated PAPs can be included as appendicies to published papers, which sometimes present different analyses from those specified in the pre-analysis plan.

This populated PAP was written for an already-published study. Bonilla and Tillery (2020) estimated the causal effects of alternative framings of Black Lives Matter (BLM) on support for the movement among Black Americans overall and among subsets of the Black community. The authors of that study posted a preanalysis plan to the As Predicted registry: link. To illustrate how to write a preanalysis plan using the MIDA framework, we made an alternative PAP. This populated pap analyzes the data according to the specifications in that alternative PAP.

```
library(tidyverse)
library(coefplot)
library(estimatr)
library(knitr)
library(kableExtra)
library(modelsummary)
library(rdss)
# load the real data
data(bonilla_tillery)
```

Average effects

The table below shows a mock analysis of average effects (estimated with and without covariate adjustment) as well as the heterogeneous effects analyses with respect to the quasi-continuous moderators.

```
fit_1 <- lm_robust(blm_support ~ Z, data = bonilla_tillery)
fit_2 <- lm_robust(blm_support ~ Z + female + lgbtq + age +
                     religiosity + income + college + linked_fate +
                     blm_familiarity, data = bonilla_tillery)
modelsummary(models = list("DIM" = fit_1, "OLS" = fit_2), output = "markdown",
             coef_omit = "female|lgbtq|age|religiosity|income|college|linked_fate|blm_familiarity",
             stars = TRUE)
```

	DIM	OLS
(Intercept)	0.842***	0.408***
	(0.015)	(0.043)
Znationalism	-0.012	-0.002
	(0.021)	(0.019)
Zfeminism	-0.036	-0.014
	(0.022)	(0.020)
Zintersectional	-0.037+	-0.031

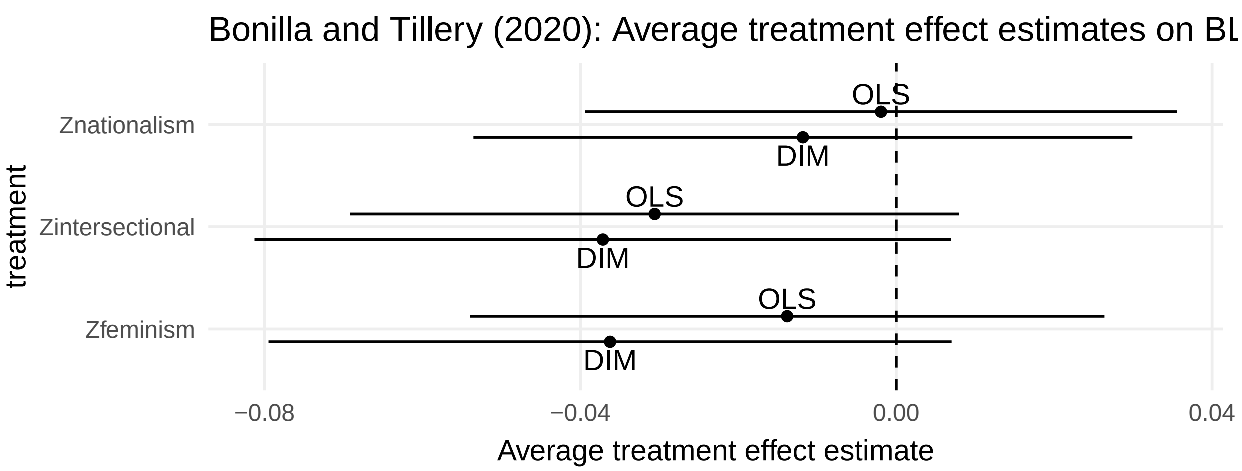
*For Blair, Coppock, and Humphreys, *Research Design in the Social Sciences: Declaration, Diagnosis, and Redesign.*

	DIM	OLS
	(0.022)	(0.020)
Num.Obs.	849	849
R2	0.005	0.203
R2 Adj.	0.001	0.193
AIC	-96.2	-268.9
BIC	-72.5	-207.2
RMSE	0.23	0.20

Note: ^^ + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

```
ates <-
  list("DIM" = fit_1, "OLS" = fit_2) %>%
  map_df(tidy, .id = "estimator") %>%
  filter(term %in% c("Znationalism", "Zfeminism", "Zintersectional"))

ggplot(ates, aes(estimate, term, group = estimator)) +
  geom_point(position = position_dodgev(height = 0.5)) +
  geom_linerange(aes(xmin = conf.low, xmax = conf.high),
                 position = position_dodgev(height = 0.5)) +
  geom_text(aes(label = estimator), position = position_dodgev(height = 1.2)) +
  geom_vline(xintercept = 0, linetype = "dashed") +
  theme_dd() +
  labs(x = "Average treatment effect estimate",
       y = "treatment",
       title = "Bonilla and Tillery (2020): Average treatment effect estimates on BLM support")
```



Heterogeneous effects

Here we run regressions of the outcome on the treatment, the covariate, and the interaction between the treatment and the covariate.

```
fit_3 <- lm_robust(blm_support ~ Z * linked_fate, data = bonilla_tillery)
fit_4 <- lm_robust(blm_support ~ Z * blm_familiarity, data = bonilla_tillery)
fit_5 <- lm_robust(blm_support ~ Z * female, data = bonilla_tillery)
fit_6 <- lm_robust(blm_support ~ Z * lgbtq, data = bonilla_tillery)
modelsummary(models = list(fit_3, fit_4, fit_5, fit_6), output = "markdown", stars = TRUE)
```

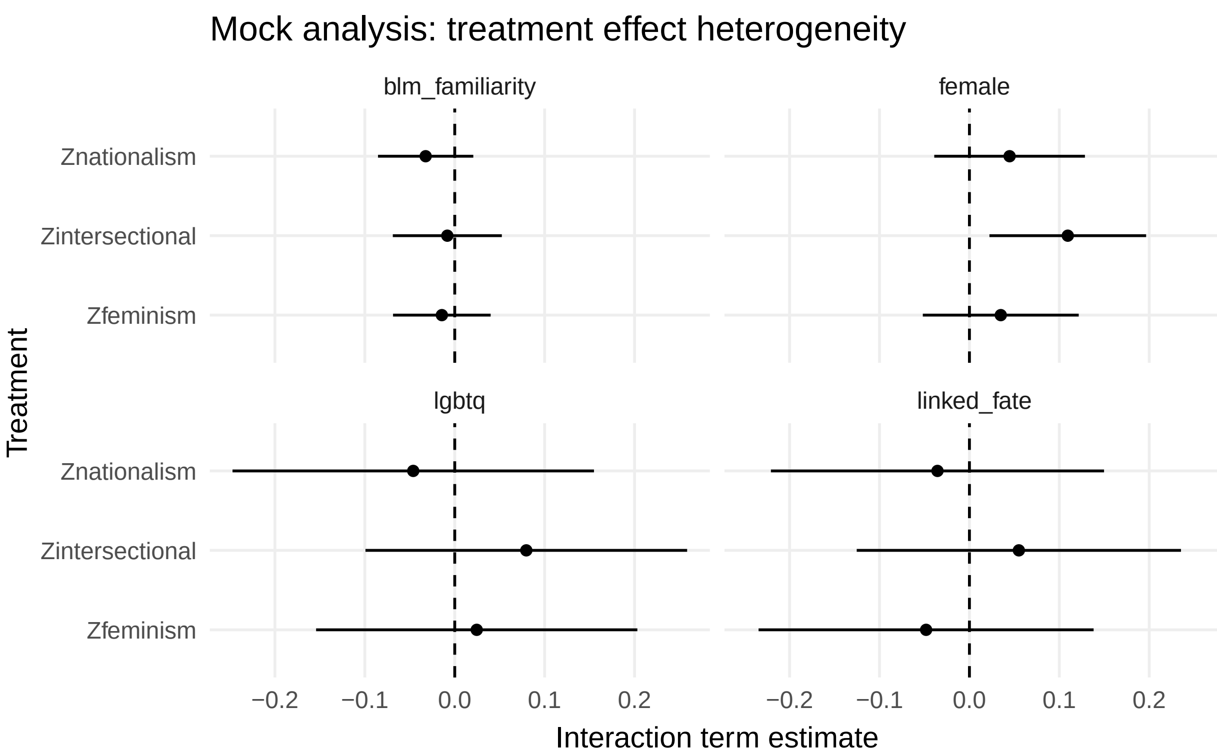
	Model 1	Model 2	Model 3	Model 4
(Intercept)	0.606***	0.536***	0.851***	0.841***
	(0.062)	(0.068)	(0.023)	(0.016)
Znationalism	0.020	0.092	-0.035	-0.009
	(0.084)	(0.089)	(0.030)	(0.022)
Zfeminism	0.012	0.021	-0.054+	-0.038+
	(0.082)	(0.090)	(0.031)	(0.023)
Zintersectional	-0.079	-0.007	-0.091**	-0.043+
	(0.081)	(0.100)	(0.034)	(0.023)
linked_fate	0.300***			
	(0.071)			
Znationalism × linked_fate	-0.036			
	(0.094)			
Zfeminism × linked_fate	-0.048			
	(0.095)			
Zintersectional × linked_fate	0.055			
	(0.092)			
blm_familiarity		0.099***		
		(0.020)		
Znationalism × blm_familiarity		-0.032		
		(0.027)		
Zfeminism × blm_familiarity		-0.014		
		(0.028)		
Zintersectional × blm_familiarity		-0.008		
		(0.031)		
female			-0.016	
			(0.031)	
Znationalism × female			0.045	
			(0.043)	
Zfeminism × female			0.035	
			(0.044)	
Zintersectional × female			0.109*	
			(0.044)	
lgbtq				0.023
				(0.080)
Znationalism × lgbtq				-0.046
				(0.102)
Zfeminism × lgbtq				0.024
				(0.091)
Zintersectional × lgbtq				0.080
				(0.091)
Num.Obs.	849	849	849	849
R2	0.141	0.093	0.017	0.009
R2 Adj.	0.134	0.085	0.009	0.001
AIC	-213.1	-166.6	-98.6	-91.9
BIC	-170.4	-123.9	-55.9	-49.2
RMSE	0.21	0.22	0.23	0.23

Note: ^^ + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This figure is a coefficient plot of the estimated coefficient on the treatment by covariate interaction term.

```r
cates <-
  list(fit_3, fit_4, fit_5, fit_6) %>%
  map_df(tidy) %>%
  filter(grepl(pattern = ":", term)) %>%
  separate(term, into = c("treatment", "covariate"), sep = ":")

ggplot(cates, aes(estimate, treatment)) +
  geom_point() +
  geom_linerange(aes(xmin = conf.low, xmax = conf.high)) +
  geom_vline(xintercept = 0, linetype = "dashed") +
  facet_wrap(~covariate) +
  theme_dd() +
  labs(x = "Interaction term estimate",
       y = "Treatment",
       title = "Mock analysis: treatment effect heterogeneity")
```



References

Banerjee, Abhijit, Esther Duflo, Amy Finkelstein, Lawrence F Katz, Benjamin A Olken, and Anja Sautmann. 2020. "In Praise of Moderation: Suggestions for the Scope and Use of Pre-Analysis Plans for RCTs in Economics." Working Paper 26993. Working Paper Series. National Bureau of Economic Research. https://doi.org/10.3386/w26993.

Bonilla, Tabitha, and Alvin B. Tillery. 2020. "Which Identity Frames Boost Support for and Mobilization in the #BlackLivesMatter Movement? An Experimental Test." *American Political Science Review* 114 (4): 947–62. https://doi.org/10.1017/S0003055420000544.