Example Preanalyis Plan*

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This document offers an example preanalysis plan (PAP) using the MIDA framework. First, it explains the design in terms of its model, inquiries, data strategy, and answer strategy. Then, it declares the design in code using the `DeclareDesign` package for R. It draws simulated data from the design, then produces analysis tables and figures. Finally, the pap offers a design diagnosis to convey ex-ante beliefs about the power of the study. While a design diagnosis is not a necessary component of a preanalysis plan, it can be useful to show readers why a particular design was chosen over others.

This example 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. These study authors are models of research transparency: they prominently link to the PAP in the published article, they conduct no non-preregistered analyses except those requested during the review process, and their replication archive includes all materials required to confirm their analyses, all of which we were able to reproduce exactly with minimal effort. Our goal with this section is to show how design declaration can supplement and complement existing planning practices.

The purpose of this document is to not to criticize the original author's PAP, but instead to show how to produce a preanalysis plan using design declaration and diagnosis. The advantage of using an already published study is that we can use the same study to describe how to construct a populated PAP (Banerjee et al. (2020)) and how to reconcile the pre-registered and the reported analyses.

Study design

In this section, we describe the study in terms of its model, inquiry, data strategy, and answer strategy.

Model

This study employs a model of coalition politics that emphasizes the tensions induced by overlapping group identities. Framing the BLM movement as feminist or pro-LGBTQ may increase support among Black women or Black LGBTQ identifiers, but that increase may come at the expense of support among Black men or Black Americans who do not identify as LGBTQ. Similarly, this model predicts that subjects with stronger attachment to their Black identity will have a larger response to a Black nationalist framing of BLM than those with weaker attachments. The model also includes beliefs about the distributions of gender, LGBTQ status, and Black identity strength. Other background characteristics that may be correlated with BLM support include age, religiosity, income, education, and familiarity with the movement.

The study's focus in on the causal effects of nationalism, feminism, and intersectional frames relative to a general description of the Black Lives Matter movement. These effects are supposed to be different for different kinds of people. The effect of the nationalism treatment is hypothesized to be stronger, the greater subjects' sense of linked fate; the effect of the feminism treatment should be negative for men but positive for women; the effect of the intersectionality treatment should be positive for LGBTQ identifiers, but negative for non-identifiers.

*For Blair, Coppock, and Humphreys, *Research Design: Declaration, Diagnosis, Redesign.*

Inquiries

The inquiries for this study include the average effects of all three treatments relative to the "general" framing, as well as the differences in average effects for subgroups. The inquires all are all sample average treatment effects, rather than population average treatment effects. That is, the study does not formally extrapolate from the sample of Black Americans to the population of all Black Americans.

Data strategy

This study's subjects are 800 Black Americans recruited by the survey firm Qualtrics using a quota sampling procedure. After subjects' background characteristics are measured, they will be assigned to one of four treatment conditions. Since the survey was conducted on Qualtrics, we assume that the authors used the built-in randomization tools, which use simple (Bernoulli) random assignment.

Answer Strategy

The answer strategy is a series of OLS regressions. The average treatment effects of each treatment will be assesd with OLS regression of othe outcome variables on treatment, with and without controls for pre-treatment characteristics. The differences-in-CATEs will be estimated with OLS that include interaction terms between the moderators and the treatment variables.

Design declaration

In this section we formally declare the design in code.

Model

```
library(tidyverse)
library(DeclareDesign)
library(rdddr)
library(modelsummary)
library(knitr)
library(kableExtra)
library(coefplot)

# helper functions
rescale <- function(x) {
  (x - min(x)) / (max(x) - min(x))
}

likert_cut <- function(x) {
  as.numeric(cut(x, breaks = c(-100, 0.1, 0.3, 0.6, 0.8, 100), labels = 1:5))
}

model <-
  declare_model(
    N = 800,
    # these are covariates
    female = rbinom(N, 1, prob = 0.51),
    lgbtq = rbinom(N, 1, prob = 0.05),
    linked_fate = sample(1:5, N, replace = TRUE,
                         prob = c(0.05, 0.05, 0.15, 0.25, 0.5)),
    age = sample(18:80, N, replace = TRUE),
    religiosity = sample(1:6, N, replace = TRUE),
    income = sample(1:12, N, replace = TRUE),
    college = rbinom(N, 1, prob = 0.5),
    blm_familiarity = sample(1:4, N, replace = TRUE),
    U = runif(N),
    blm_support_latent = rescale(
      U + 0.1 * blm_familiarity +
        0.45 * linked_fate +
        0.001 * age +
        0.25 * lgbtq +
        0.01 * income +
        0.1 * college +
        -0.1 * religiosity),
    # potential_outcomes
    blm_support_Z_general =
      likert_cut(blm_support_latent),
    blm_support_Z_nationalism =
      likert_cut(blm_support_latent + 0.01 +
                   0.01 * linked_fate +
                   0.01 * blm_familiarity),
    blm_support_Z_feminism =
      likert_cut(blm_support_latent - 0.02 +
                   0.07 * female +
                   0.01 * blm_familiarity),
    blm_support_Z_intersectional =
      likert_cut(blm_support_latent  - 0.05 +
                   0.15 * lgbtq +
                   0.01 * blm_familiarity)
  )
```

Inquiry

```
# This function allows us to specify interaction inquiries
# in the same way for both discrete and continuous variables
slope <- function(y, x) { cov(y, x) / var(x) }

inquiry <-
  declare_inquiries(
    # Average effects
    ATE_nationalism =
      mean(blm_support_Z_nationalism - blm_support_Z_general),
    ATE_feminism =
      mean(blm_support_Z_feminism - blm_support_Z_general),
    ATE_intersectional =
      mean(blm_support_Z_intersectional - blm_support_Z_general),

    # Overall heterogeneity w.r.t. blm_familiarity
    DID_nationalism_familiarity =
      slope(blm_support_Z_nationalism - blm_support_Z_general,
            blm_familiarity),
    DID_feminism_familiarity =
      slope(blm_support_Z_feminism - blm_support_Z_general,
            blm_familiarity),
    DID_intersectional_familiarity =
      slope(blm_support_Z_intersectional - blm_support_Z_general,
            blm_familiarity),

    # Treatment-specific heterogeneity
    DID_nationalism_linked_fate =
      slope(blm_support_Z_nationalism - blm_support_Z_general,
            linked_fate),
    DID_feminism_gender =
      slope(blm_support_Z_feminism - blm_support_Z_general,
            female),
    DID_intersectional_lgbtq =
      slope(blm_support_Z_intersectional - blm_support_Z_general,
            lgbtq)
  )
```

Data strategy

Note that we did not explicitly model the quota sampling step from qualtrics.

```
data_strategy <-
  declare_assignment(
    Z = simple_ra(
      N,
      conditions =
        c("general", "nationalism", "feminism", "intersectional"),
      simple = TRUE
    )
  ) +
  declare_measurement(blm_support = reveal_outcomes(blm_support ~ Z))
```

Answer strategy

```
answer_strategy <-
  declare_estimator(
    blm_support ~ Z,
    term = c("Znationalism", "Zfeminism", "Zintersectional"),
    inquiry =
      c("ATE_nationalism", "ATE_feminism", "ATE_intersectional"),
    label = "OLS") +
  declare_estimator(
    blm_support ~ Z + age + female + as.factor(linked_fate) + lgbtq,
    term = c("Znationalism", "Zfeminism", "Zintersectional"),
    inquiry =
      c("ATE_nationalism", "ATE_feminism", "ATE_intersectional"),
    label = "OLS with controls") +
  declare_estimator(
    blm_support ~ Z*blm_familiarity,
    term = c("Znationalism:blm_familiarity",
             "Zfeminism:blm_familiarity",
             "Zintersectional:blm_familiarity"),
    inquiry = c("DID_nationalism_familiarity",
                "DID_feminism_familiarity",
                "DID_intersectional_familiarity"),
    label = "DID_familiarity") +
  declare_estimator(
    blm_support ~ Z * linked_fate,
    term = "Zfeminism:linked_fate",
    inquiry = "DID_nationalism_linked_fate",
    label = "DID_nationalism_linked_fate") +
  declare_estimator(
    blm_support ~ Z * female,
    term = "Zfeminism:female",
    inquiry = "DID_feminism_gender",
    label = "DID_feminism_gender") +
  declare_estimator(
    blm_support ~ Z * lgbtq,
    term = "Zintersectional:lgbtq",
    inquiry = "DID_intersectional_lgbtq",
    label = "DID_intersectional_lgbtq")
```

Full Declaration

```
declaration <- model + inquiry + data_strategy + answer_strategy
```

Mock data analysis

Here we draw a mock dataset from the declaration above.

```
set.seed(343)
mock_data <- draw_data(declaration)
```

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

	DIM	OLS
(Intercept)	3.559***	1.132***
	(0.047)	(0.100)
Znationalism	0.425***	0.364***
	(0.080)	(0.046)
Zfeminism	0.216**	0.167***
	(0.075)	(0.048)
Zintersectional	-0.054	-0.060
	(0.077)	(0.045)
Num.Obs.	800	800
R2	0.050	0.680
R2 Adj.	0.046	0.676
Std.Errors	HC2	HC2

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

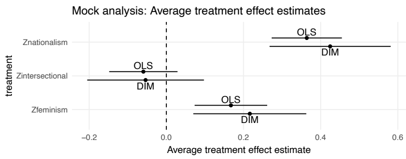


Figure 1: Mock coefficient plot from Bonilla and Tillery design.

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

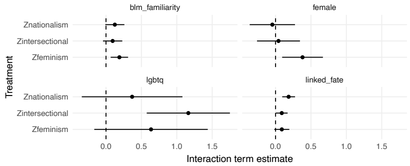
	Model 1	Model 2	Model 3	Model 4
(Intercept)	1.766***	3.450***	3.589***	3.560***
	(0.112)	(0.111)	(0.069)	(0.048)
Znationalism	-0.329+	0.092	0.441***	0.404***
	(0.190)	(0.195)	(0.105)	(0.082)
Zfeminism	-0.179	-0.250	0.045	0.197**
	(0.223)	(0.167)	(0.107)	(0.076)
Zintersectional	-0.377*	-0.286	-0.074	-0.124
	(0.165)	(0.181)	(0.111)	(0.078)
linked_fate	0.441***			
	(0.029)			
Znationalism × linked_fate	0.185***			
	(0.046)			
Zfeminism × linked_fate	0.088			
	(0.054)			
Zintersectional × linked_fate	0.088*			
	(0.042)			
blm_familiarity		0.044		
		(0.041)		
Znationalism × blm_familiarity		0.125+		
		(0.069)		
Zfeminism × blm_familiarity		0.189**		
		(0.063)		
Zintersectional × blm_familiarity		0.094		
		(0.069)		
female			-0.060	
			(0.094)	
Znationalism × female			-0.045	
			(0.163)	
Zfeminism × female			0.381**	
			(0.147)	
Zintersectional × female			0.041	
			(0.154)	
lgbtq				-0.060
				(0.229)
Znationalism × lgbtq				0.369
				(0.362)
Zfeminism × lgbtq				0.636
				(0.408)
Zintersectional × lgbtq				1.163***
				(0.299)
Num.Obs.	800	800	800	800
R2	0.560	0.096	0.060	0.082
R2 Adj.	0.556	0.088	0.052	0.074
Std.Errors	HC2	HC2	HC2	HC2

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.

```
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")
```



Design diagnosis

In this section we describe the power for the chosen design. The diagnosis indicates that the design produces unbiased estimates but is better powered from some inquires than others (under the above assumptions about effect size, which were our own and not the original authors'). We are well-powered for the average effects, and the power increases when we include covariate controls. The design is probably too small for most of the heterogeneous effect analyses, which is a point directly conceded in the authors' original PAP.

```
diagnosis <-
  declaration %>%
  diagnose_design()
```

```
diagnosis %>%
  reshape_diagnosis() %>%
  select(Inquiry, `Mean Estimand`, Estimator, Bias, Power) %>%
  kable(
    booktabs = TRUE,
    align = "r",
    digits = 3,
    caption = "Design diagnosis for Bonilla and Tillery design."
  )%>%
  kable_styling(latex_options = "HOLD_position")
```

Table 3: Design diagnosis for Bonilla and Tillery design.

Inquiry	Mean Estimand	Estimator	Bias	Power
ATE_feminism	0.18	OLS	0.00	0.59
	(0.00)		(0.00)	(0.02)
ATE_feminism	0.18	OLS with controls	0.00	0.88
	(0.00)		(0.00)	(0.01)
ATE_intersectional	-0.08	OLS	0.01	0.15
	(0.00)		(0.00)	(0.02)
ATE_intersectional	-0.08	OLS with controls	0.00	0.26
	(0.00)		(0.00)	(0.02)
ATE_nationalism	0.33	OLS	0.00	0.97
	(0.00)		(0.00)	(0.01)
ATE_nationalism	0.33	OLS with controls	0.00	1.00
	(0.00)		(0.00)	(0.00)
DID_feminism_familiarity	0.04	DID_familiarity	-0.00	0.08
	(0.00)		(0.00)	(0.01)
DID_feminism_gender	0.30	DID_feminism_gender	-0.00	0.44
	(0.00)		(0.01)	(0.02)
DID_intersectional_familiarity	0.04	DID_familiarity	-0.00	0.07
	(0.00)		(0.00)	(0.01)
DID_intersectional_lgbtq	0.57	DID_intersectional_lgbtq	0.01	0.36
	(0.00)		(0.02)	(0.02)
DID_nationalism_familiarity	0.03	DID_familiarity	-0.00	0.09
	(0.00)		(0.00)	(0.01)
DID_nationalism_linked_fate	0.06	DID_nationalism_linked_fate	-0.05	0.06
	(0.00)		(0.00)	(0.01)

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.