ADDENDUM TO:

Pre-Analysis Plan (PAP) for:

A Pair-Matched Randomized Evaluation of Faith-Based Couples Counselling in Uganda

THIS **ADDENDUM** TO PRE-ANALYSIS PLAN WAS FIRST REGISTERED
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Behavioral Game

Background:

A principal finding from the analysis of the Becoming One (B1) midline survey was a reported shift in power dynamics within couples: women and men reported that women were more likely to be involved in decision-making around men's finances. We hypothesized that this increased involvement reflected an increased willingness on the part of men to involve women in financial decisions.

To validate this finding with a behavioral measure, we plan to conduct a game in which we measure men's willingness to share decision-making around spending of men's income during endline data collection. The purpose of the game is to model a common situation among couples in which there is a large income disparity in favor of men: lending money to women for purchasing household items. If we find that men become more likely to delegate decision-making over real income to their female partners as a result of B1, we will interpret this as strong behavioral evidence in favor of one of the main survey results.

Game Description:

During the endline survey, we give both men and women ten numbered coins, each worth 1,000 UGX. We present them with a list of nine goods: three are valued at 1,000 UGX, three at 2,000 UGX, and three at 3,000 UGX. We ask respondents to place these coins on the list in order of preference (e.g., "What is the first good you would like to spend the money on? If it is worth 3000, coins 1,2,3 would be spent on that good" and so on).

At the end of the endline survey with men, men are told that we wish to thank them for their participation by allowing them to choose from the same list of nine goods using a fixed budget of 10,000 UGX. Before purchasing, men have the option to delegate a portion of their budget (in 1,000 UGX coins) to their partner, with the understanding we will use the budget allocated to her to purchase the goods according to her ranked preferences. The steps will work as follows:

1. Man looks at the list of goods and the prices
2. Man decides how much to delegate to the wife
3. Man puts coins on the list (in order of preference of goods) until he exhausts the budget he kept for himself. At this point the man knows that he will actually receive the goods he is choosing.
4. Next, we ask a hypothetical question asking how would he allocate the rest of the coins (the ones he had delegated to wife) if he were to spend that money too.
5. Next we ask him if he were to give the 10 coins to his wife, how she would spend the money on these goods (simulating the procedure from 4).

We also collect data on men’s beliefs about his partner’s preferences by asking them to perform the same coin-placing task from her perspective.

Main Analyses

The game is meant to mimic men's decisions sharing income that they have the option to privately consume. The amount of money that he "delegates" to his partner is thought of as a behavioral proxy for his willingness to cede control over decision-making about his earnings. Our main research question is:

- **Delegation**: Do men who went through B1 delegate more to their partner than those who did not?

- **Representation**: Do the bundles of goods purchased by couples who went through B1 more closely reflect the preferences of women than those who did not?

We also intend to analyze secondary questions, namely:

- **Alignment**: Do men and women's preferences about purchase decisions become more aligned due to B1?

- **Information**: Are men better able to anticipate the spending preferences of their partner?

We describe the specific measures for these outcomes below.

Sub-study: Public vs. Gendered Goods

We also plan to vary the game by randomizing the list of goods offered to couples. Specifically couples will be randomized to one of four goods conditions:
- Public goods
- Public goods and men's private goods
- Public goods and women's private goods
- Public goods and men's and women's private goods

The idea with the private treatments is to manipulate men's perception of risks associated with delegation.

List 1. Public goods

Goods	Price (UGX)	Type
5 Pencils	1000	Household
Glass	1000	Household
Strainer	1000	Household
Soap	2000	Household

2 forks and 2 spoons	2000	Household
Toothpaste	2000	Household
Plate	3000	Household
Detergent	3000	Household
Jelly	3000	Household

List 2. Public goods + women's private goods

Goods	Price (UGX)	Type
Glass	1000	Household
Hair Comb	1000	Women's
Women's wallet	1000	Women's
Soap	2000	Household
Hair Conditioner	2000	Women's
Nail Polish	2000	Women's
Plate	3000	Household
Sanitary Pads	3000	Women's
Movit hair food	3000	Women's

List 3. Public goods + men's private goods

Goods	Price (UGX)	Type
Glass	1000	Household
Scratcher	1000	Men's
Airtime	1000	Men's
Soap	2000	Household
Soccer Poster	2000	Men's
Playing cards	2000	Men's
Plate	3000	Household
Men's socks	3000	Men's
Key chain	3000	Men's

List 4. Public goods + women's + men's private goods

Goods	Price (UGX)	Type
Glass	1000	Household
Hair Comb	1000	Women's
Scratcher	1000	Men's

Soap	2000	Household
Soccer Poster	2000	Women's
Hair Conditioner	2000	Men's
Plate	3000	Household
Sanitary Pads	3000	Women's
Men's socks	3000	Men's

Sample Selection

We intend to play the game with all 2,458 couples in cohorts 1, 2, and 3 (including those in the Faith Leader "buffer" groups and those who were non-randomly assigned to cohort 2). The only people from the original recruitment class that we will not contact are those who declined participation in the research or those who were ineligible for the study.

We have two main reasons for including the full study sample:

1. There were equity concerns about playing a game in which couples would receive material benefits if only some, but not all, couples would be able to participate.

2. The larger sample increases the power to detect effects for some of the estimands related to the game, which allows us to ask *a priori* slightly more nuanced questions.

Randomization

Couples will be randomized to one of the four goods list conditions using the randomization code attached at the end of this document.

Estimation

For analyses related to the effect of B1 on preferences and game behavior, our estimands of interest are of the form:

$$E[Y_i(Z_i = 1) - Y_i(Z_i = 0)]$$

Which represents the intention-to-treat effect of random assignment to cohort one of B1. Our main estimator is the "covariate-adjusted specification" discussed in the main Pre-Analysis Plan, which adjusts for predictive covariates using a mean-centering and interaction approach described in Lin (2013). This specification will serve as the basis for inference about the treatment effects. These analyses will principally be among just cohort 1 and 3 couples as these formed the basis of the original experimental sample.

For transparency, we will also report (in main table or appendix) effects from a minimal, design-based estimator that only accounts for the randomization and does not adjust for covariates. The two estimators can be written as follows:

1. Covariate-adjusted specification: $y_{ij} = \gamma_j + \tau z_i + \beta' \overline{x}_i + \lambda' \overline{x}_i z_i + \varepsilon_i$
2. Design-based specification: $y_{ij} = \gamma_j + \tau z_i + \varepsilon_i$

Where γ is a block-level fixed effect, τ is the average treatment effect, z is an indicator of assignment to cohort 1, $\overline{x}$ is a vector of mean-centered covariates, and ε an error term. The index i indicates individuals and couples in individual- and couple-level analyses, respectively. The index j indicates matched pair blocks from the original randomization.

For analyses related to the sub-study on the effects of the composition of goods on allocation and decision-making we have several estimands of interest:

A. Effect of availability of men's goods relative to only public goods $E[Y_i(Z_i^* = 1) - Y_i(Z_i^* = 0)]$
B. Effect of availability of women's goods relative to only public goods $E[Y_i(Z_i^* = 2) - Y_i(Z_i^* = 0)]$
C. The interactive effect of including women's goods on the effect of including men's goods relative to only public goods $E[(Y_i(Z_i^* = 3) - Y_i(Z_i^* = 2)) - (Y_i(Z_i^* = 1) - Y_i(Z_i^* = 0))]$

Where Z_i^* represents the assignment to public goods ($Z_i^* = 0$), public + men's goods ($Z_i^* = 1$), public + women's goods ($Z_i^* = 2$), public + men's + women's goods ($Z_i^* = 3$).

The primary estimator for A and B will involve coding variable z_i in regression specifications 1 and 2 above to be dummy indicators for "any men's goods" (Z_star equal to 3 or 1 versus 2 or 0) and "any women's goods" (Z_star equal to 3 or 2 versus 1 or 0), respectively. For unbiasedness, this estimation approach assumes an interaction effect of zero. Should we find statistically significant evidence of an interaction in estimates of C at the alpha = .05 level, we will use a fully interacted model as the main regression specification for A, B, and C.

Statistical Inference

As described in the main PAP, in all couple-level analyses, we will calculate standard errors using a heteroskedasticity-robust (HC2) estimator as coded in `estimatr` for R. In all individual-level analyses, we will calculate cluster-robust standard errors (CR2).

Decisions about the significance of effect sizes will rely primarily on non-parametric *p*-values calculated using randomization inference. We will conduct one-tailed, positive tests for all of the outcomes listed below.

Outcome Coding

- **Delegation**:
    - an integer count of the number of tokens delegated to the female partner [0,10]

- **Representation**:
    - The first measure will translate women's preferences into a set of coins that would have been spent on goods under a full delegation of 10 coins. For example, if a woman would have preferred two goods each of A and B valued at 1000 UGX, and two goods of C valued at 3000 UGX, but the eventual purchase after delegation only includes one good A and one good C, then 4/10 = 40% of coins were spent in accordance with her preferences.
    - The second measure will be calculated as before, except that every coin will be weighted, in order, by (11 - x)/55, where x is the rank of the coin and 55 is the sum of 1...10. Thus, for example, if the woman puts her first six coins on C and her last four coins on A and B, and four of A and B and none of C are bought, then rather than 40%, we would calculate a preference rank-weighted average: (11-7)/55 + (11-8)/55 + (11-9)/55 + (11-10)/55 = 18%

- **Alignment in preferences**:
    - For this measure, we cross tabulate the number of coins that men and women put on goods A, B, C, D, E, F, G, H, and I, as a measure of **their own** preferences and sum the diagonal of the matrix then divide by 10. Thus, if a man puts five coins on A, and five on B, and the woman puts three on A, two on B, and five on C, the diagonal of the cross-tabulation will be 3 2 0 0 0 0 0 0 0 and so the measure will sum to five. We will refer to this as 5/10 = 50% alignment.

- **Information about preferences**:
    - We will construct this measure in the same way as for alignment, but this time cross-tabulating men's appraisal of women's preferences with women's preferences.

Blocking and Randomization Code

```
rm(list = ls())

# Setup and load baseline data ---------------------------------------------

speed_run <- TRUE
post_blind <- TRUE
rerun_baseline_cleaning <- FALSE

source("06_midline/00_load_data_and_packages/01_load_packages.R")
source("06_midline/00_load_data_and_packages/02_load_data.R")


# Create blocking variable -------------------------------------------------

# in this scetion we recreate the control_index outcome specified in PAP
# using the baseline data as this will form the basis for blocking
blw$dm_earnings_resp_i_w <- case_when(
      blw$dm_earnings_resp_2_w == 1 ~ 0,
      blw$dm_earnings_resp_2_w == 0 ~ 1,
      TRUE ~ NA_real_
)
blw$dm_earnings_partners_i_w <- case_when(
      blw$dm_earnings_partners_2_w == 1 ~ 0,
      blw$dm_earnings_partners_2_w == 0 ~ 1,
      TRUE ~ NA_real_
)
blw$dm_large_purchase_i_w <- case_when(
      blw$dm_large_purchase_2_w == 1 ~ 0,
      blw$dm_large_purchase_2_w == 0 ~ 1,
      TRUE ~ NA_real_
)
blw$dm_health_i_w <- case_when(
      blw$dm_health_2_w == 1 ~ 0,
      blw$dm_health_2_w == 0 ~ 1,
      TRUE ~ NA_real_
)
blw$dm_visit_family_i_w <- case_when(
      blw$dm_visit_family_2_w == 1 ~ 0,
      blw$dm_visit_family_2_w == 0 ~ 1,
      TRUE ~ NA_real_
)
```

```
blw$dm_windfall_resp_i_w <- case_when(
      blw$dm_windfall_resp_2_w == 1 ~ 0,
      blw$dm_windfall_resp_2_w == 0 ~ 1,
      TRUE ~ NA_real_
)
blw$dm_windfall_partner_i_w <- case_when(
      blw$dm_windfall_partner_2_w == 1 ~ 0,
      blw$dm_windfall_partner_2_w == 0 ~ 1,
      TRUE ~ NA_real_
)

# dm_earnings_resp_m_i = 1 if female partner makes or is involved in
decision-making; 0 otherwise;
# dm_earnings_partners_m_i = 1 if female partner makes or is involved in
decision-making; 0 otherwise;
# dm_large_purchase_m_i = 1 if female partner makes or is involved in
decision-making; 0 otherwise;
# dm_health_m_i = 1 if female partner makes or is involved in
decision-making; 0 otherwise;
# dm_visit_family_m_i = 1 if female partner makes or is involved in
decision-making; 0 otherwise;
# dm_windfall_resp_m_i = 1 if female partner makes or is involved in
decision-making; 0 otherwise;
# dm_windfall_partner_m_i = 1 if female partner makes or is involved in
decision-making; 0 otherwise.

blw$dm_earnings_resp_i_m <- case_when(
      blw$dm_earnings_resp_2_m == 1 | blw$dm_earnings_resp_3_m == 1 ~ 1,
      blw$dm_earnings_resp_2_m == 0 & blw$dm_earnings_resp_3_m == 0 ~ 0,
      TRUE ~ NA_real_
)
blw$dm_earnings_partners_i_m <- case_when(
      blw$dm_earnings_partners_2_m == 1 | blw$dm_earnings_partners_2_m == 1 ~
1,
      blw$dm_earnings_partners_2_m == 0 & blw$dm_earnings_partners_2_m == 0 ~
0,
      TRUE ~ NA_real_
)
blw$dm_large_purchase_i_m <- case_when(
      blw$dm_large_purchase_2_m == 1 | blw$dm_large_purchase_2_m == 1 ~ 1,
      blw$dm_large_purchase_2_m == 0 & blw$dm_large_purchase_2_m == 0 ~ 0,
      TRUE ~ NA_real_
)
```

```
blw$dm_health_i_m <- case_when(
      blw$dm_health_2_m == 1 | blw$dm_health_2_m == 1 ~ 1,
      blw$dm_health_2_m == 0 & blw$dm_health_2_m == 0 ~ 0,
      TRUE ~ NA_real_
)
blw$dm_visit_family_i_m <- case_when(
      blw$dm_visit_family_2_m == 1 | blw$dm_visit_family_2_m == 1 ~ 1,
      blw$dm_visit_family_2_m == 0 & blw$dm_visit_family_2_m == 0 ~ 0,
      TRUE ~ NA_real_
)
blw$dm_windfall_resp_i_m <- case_when(
      blw$dm_windfall_resp_2_m == 1 | blw$dm_windfall_resp_2_m == 1 ~ 1,
      blw$dm_windfall_resp_2_m == 0 & blw$dm_windfall_resp_2_m == 0 ~ 0,
      TRUE ~ NA_real_
)
blw$dm_windfall_partner_i_m <- case_when(
      blw$dm_windfall_partner_2_m == 1 | blw$dm_windfall_partner_2_m == 1 ~
1,
      blw$dm_windfall_partner_2_m == 0 & blw$dm_windfall_partner_2_m == 0 ~
0,
      TRUE ~ NA_real_
)

blw$fin_control_i_w <- case_when(
      blw$fin_control_w == 1 ~ 1,
      blw$fin_control_w == 2 ~ 0.5,
      blw$fin_control_w == 3 ~ 0
)

blw$fin_control_work_i_w <- case_when(
      blw$fin_control_work_w == 0 ~ 1,
      blw$fin_control_work_w == 1 ~ 0
)

blw$fin_control_take_money_i_w <- case_when(
      blw$fin_control_take_money_w == 0 ~ 1,
      blw$fin_control_take_money_w == 1 ~ 0
)

blw$fin_control_keep_money_i_w <- case_when(
      blw$fin_control_keep_money_w == 0 ~ 1,
      blw$fin_control_keep_money_w == 1 ~ 0
)
```

```
blw$control_friends_i_w <- case_when(
      blw$control_friends_w == 0 ~ 1,
      blw$control_friends_w == 1 ~ 0
)

blw$control_family_i_w <- case_when(
      blw$control_family_w == 0 ~ 1,
      blw$control_family_w == 1 ~ 0
)

blw$control_whereabouts_i_w <- case_when(
      blw$control_whereabouts_w == 0 ~ 1,
      blw$control_whereabouts_w == 1 ~ 0
)

blw$control_mobile_i_w <- case_when(
      blw$control_mobile_w == 0 ~ 1,
      blw$control_mobile_w == 1 ~ 0
)

blw$income_r_sep_amt_i_m <- NA
blw$income_r_sep_amt_i_m[blw$income_r_sep_amt_m == 0] <- 1
blw$income_r_sep_amt_i_m[blw$income_r_sep_amt_m == 1] <- 0

# already exists in BL
# blw$control_general_i_w <- case_when(
#     blw$control_general_w == 1 ~ 1,
#     blw$control_general_w == 2 ~ 0.66666,
#     blw$control_general_w == 3 ~ 0.33333,
#     blw$control_general_w == 4 ~ 0
# )

blw$control_index <-
      blw %>%
      select(fin_control_i_w,
                         fin_control_work_i_w,
                         fin_control_take_money_i_w,
                         fin_control_keep_money_i_w,
                         control_friends_i_w,
                         control_family_i_w,
                         control_whereabouts_i_w,
                         control_mobile_i_w,
```

```
                              dm_earnings_resp_i_w,
                              dm_earnings_partners_i_w,
                              dm_large_purchase_i_w,
                              dm_health_i_w,
                              dm_visit_family_i_w,
                              dm_windfall_resp_i_w,
                              dm_windfall_partner_i_w,
                              dm_earnings_resp_i_m,
                              dm_earnings_partners_i_m,
                              dm_large_purchase_i_m,
                              dm_health_i_m,
                              dm_visit_family_i_m,
                              dm_windfall_resp_i_m,
                              dm_windfall_partner_i_m,
                              income_r_sep_amt_i_m,
                              control_general_i_w) %>%
      rowMeans()


# Create randomization blocks based on decision-making --------------------

# Subset to those who participated in baseline
bl_sample <- select(blw, cup_id, control_index)
bl_sample <- left_join(bl_sample, cohorts, by = "cup_id")
bl_sample <- filter(bl_sample, cohort != "b1_inel")

# Block on baseline decision-making variables
block_on <- c("control_index")

bls <- blockTools::block(
      data = bl_sample,
      n.tr = 4,
      id.vars = "cup_id",
      groups = "fl_id",
      block.vars = block_on
      )

bl_sample$blocks <- blockTools::createBlockIDs(
      obj = bls,
      data = bl_sample,
      id.var = "cup_id"
      )
```

```r
# check distribution of block sizes
bl_sample %>%
      group_by(blocks) %>%
      count(name = "size") %>%
      group_by(size) %>%
      count()


# Randomize within decision-making blocks ---------------------------------

set.seed(826703)

# performs complete ra in blocks defined by baseline decision-making
# variables
bl_sample$Z_goods <-
      with(bl_sample,
                   randomizr::block_ra(
                        blocks = blocks,
                        prob_each = c(.25, .25, .25, .25),
                        conditions = c("L1", "L2", "L3", "L4")
                        )
                   )


# Create blocks for sample that didn't complete baseline ------------------

# subset to those who were not in BL but were eligible for B1
no_bl_sample <-
      filter(cohorts, (!cup_id %in% bl_sample$cup_id) &
                              cohort != "b1_inel")

# create random blocks of size 4
no_bl_sample <-
      no_bl_sample %>%
      group_by(fl_id) %>%
      mutate(
            blocks = rep(1:10, each = 4, length.out = n())
      ) %>%
      ungroup() %>%
      mutate(
            blocks = group_indices(., fl_id, blocks) + max(bl_sample$blocks)
      )
```

```
# randomize within blocks
no_bl_sample$Z_goods <-
      with(no_bl_sample,
                   randomizr::block_ra(
                        blocks = blocks,
                        prob_each = c(.25, .25, .25, .25)
                   )
      )

# check distribution of block sizes
no_bl_sample %>%
      group_by(blocks) %>%
      count(name = "size") %>%
      group_by(size) %>%
      count()


# Randomize no baseline sample --------------------------------------------

no_bl_sample$Z_goods <-
      with(no_bl_sample,
                   randomizr::block_ra(
                        blocks = blocks,
                        prob_each = c(.25, .25, .25, .25),
                        conditions = c("L1", "L2", "L3", "L4")
                   )
      )


# Combine and save --------------------------------------------------------

ra_goods <-
      bind_rows(bl_sample, no_bl_sample) %>%
      select(cup_id, fl_id, blocks, cohort, Z, Z_goods) %>%
      arrange(fl_id, cup_id)

write.csv(
      ra_goods,
      get_path("randomization/ra_goods.csv")
)
```