Framing an Unconditional Cash Transfer: Pre-Analysis Plan

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July 13, 2017

Abstract

This document describes the pre-analysis plan for a randomized experiment examining the effects of framing of welfare payments on self-concept and economic behavior. In this study, we will provide small, unconditional cash transfers to residents of an informal settlement in Nairobi and vary the way in which the transfers are framed to participants. Participants will be randomly assigned to one of three treatment groups: the transfer framed as a means toward poverty alleviation, individual empowerment, or collective support. We will then collect self-reported measures of self-efficacy, judgement, and affect and observed measures of temporal discounting and investment. This pre-analysis plan outlines our hypotheses, the schedule of experimental tasks, and our empirical strategy. In order to guarantee transparency and bind ourselves from fishing for results, we will pre-register the source files to be used for data analysis.

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1. Introduction

2. Research Design

2.1 Sampling

This study will be conducted in conjunction with the Busara Center for Behavioral Economics in Nairobi with 450 participants residing in Kibera, one of Kenya's largest urban slums (Haushofer et al. 2014). Treatment and data collection will take place with household surveys in the Kibera settlement with Busara Center enumerators. This section outlines the sampling procedure to be used in the experiment.

The study area will be partitioned into non-overlapping catchment regions to be used for sample selection. Research staff will visit one catchment region per day and will not visit the same region more than once. Beginning at a designated intersection in the catchment region, a team of nine enumerators and a guide[1] will select every eighth household in each direction for survey. From that visit on, enumerators will select the eighth house down from the subsequent structure, away from the intersection and on the opposite side of the road. If participants are not available at the selected households enumerators will move to the next door away from the origin.

Sampled individuals will be enrolled in the survey if they meet the following eligibility criteria:

1. Between 18 and 50 years old
2. Resident of Kibera
3. Not surveyed by the Busara Center for any other study in the past 10 days
4. Owns a working phone with Safaricom

If an eligible person is available at the selected household, they will be enrolled as a participant. If there are multiple members, enumerators will prioritize the youngest eligible person of the opposite gender than in the previous survey. We will sample from the study area for a total of 525 surveys.

2.2 Experimental procedure

The survey questionnaire will be delivered in English with Kiswahili translations. The following summarizes the schedule of tasks in the questionnaire.

1. **Consent agreement**
2. **Cash transfer framing**:
3. **Self-efficacy questionnaire**:
4. **Judgement questionnaire**:
5. **Affect questionnaire**:
6. **Video selection task**:
7. **Savings task**:
8. **Subjective social status ladder scale**:

[1]Guides will accompany enumerators but will not be involved in sampling or data collection.

9. **Sociodemographic questionnaire**:
10. **Frame evaluation**:
11. **Message of support**:
12. **Enumerator response**:
13. **Video task playback**:

2.3 Treatment

At the outset of the survey, eligible and consenting participants will be told they are receiving an unconditional cash transfer of KES 400 (USD PPP 10.5) from an organization unaffiliated with the Busara Center.[2] Participants will be randomly assigned to receive one of three messages introducing the purpose of the cash transfer. All frames are identical in content and structure save for the described purpose of the cash transfer. In the poverty allevation framing, the payment is described as a means to meet basic needs. The individual empowerment framing describes the payment as a means toward individual goals and the collective support framing as a means toward goals regarding family and the community.

After framing, enumerators will send USD PPP 10.5 to the participant via the mobile money system M-Pesa.[3] Enumerators will be instructed to confirm receipt of the payment. In the individual empowerment and collective support treatments, enumerators will also elicit participants to list either individual or collective goals and beliefs about the purpose of the payment.

2.3.1 Poverty alleviation framing

> The goal of this Poverty Alleviation Organization is to alleviate poverty and reduce financial hardship among the poor. This organization believes that people living in poverty should be given income support to help them meet their basic needs. This organization aims to help promote a decent standard of living among the poor and help them deal with emergencies. Thus, the Poverty Alleviation Organization gives financial assistance to people like you, to help them make ends meet. For example, with the financial assistance, people might be able to struggle less to afford basic needs, like paying off debts, paying rent, and buying clothes and food. Now we are going to send you 400 KSh. Please note that this is a one-time transfer of financial assistance.

2.3.2 Individual empowerment framing

> The goal of this Individual Empowerment Organization is to promote individuals' potential to create a better future for themselves. The organization believes that individuals are wise and know best how to help themselves become self-reliant/independent if they have the financial resources to do so. This organization aims to empower individuals to pursue their personal interests and create their own path to independence. Thus, the Individual Empowerment Organization gives financial resources to individuals, like you, to enable them to invest in their personal goals. For example, people might use their unique talents to start a self-run business, invest in job training courses, or create art. Now we are going to send you 400 KSh. Please note that this is a one-time transfer of financial resources.

[2]This study will be conducted with Kenyan shillings (KES). We report USD values calculated at purchasing power parity using a conversion factor for private consumption of 38.15 in 2013. The price level ratio of PPP conversion factor (GDP) to KES market exchange rate for 2011 was 0.444.

[3]For more information on M-Pesa, we refer the reader to Jack and Suri (2011) and Mbiti and Weil (2011).

2.3.3 Collective support framing

> The goal of this Community Empowerment Organization is to enable people to help promote better futures for those they care about and want to support most. The organization believes that people know best how to support each other and grow together if they have financial resources to do so. This organization aims to empower people to improve their own lives and those of the people and communities they care about most. Thus, the Community Empowerment Organization gives financial resources to community members, like you, to enable them to contribute positively to the lives of people important to them. For example, when people can invest in themselves, they are better able to expand employment opportunities for others, provide valuable services to their community, or teach others, including children, useful skills and knowledge. Now Community Empowerment Organization is going to send you 400 KSh. Please note that this is a one-time transfer of financial resources.

3. Data

3.1 Self-efficacy questionnaire

3.2 Judgement questionnaire

3.3 Affect questionnaire

3.4 Video selection task

3.5 Savings task

3.6 Subjective social status ladder scale

3.7 Sociodemographic questionnaire

3.8 Frame evaluation

3.9 Message of support

3.10 Beliefs about treatment

4. Empirical Analysis

4.1 Treatment effect of cash transfer frames

We will use the following reduced-form specification to estimate the treatment effect of different frames.[4]

$$Y_i = \beta_0 + \beta_1 \textsc{Ind}_i + \beta_2 \textsc{Col}_i + \varepsilon_i \tag{1}$$

Y_i refers to the outcome variables for individual i measured after the manipulation. The outcome variables described in Table 1 will be the focus of this analysis. $\textsc{Ind}_i$ indicates assignment to the individual empowerment frame while $\textsc{Col}_i$ indicates assignment to the collective support frame. The reference category in this model is the poverty alleviation frame. We will estimate cluster-robust standard errors at the individual level. Table 2 lists the hypotheses we will test using Equation 1.

To improve precision, we will also apply covariate adjustment with a vector of baseline indicators $\mathbf{X}_i$. We obtain the covariate-adjusted treatment effect estimate by estimating Equation 1 including the demeaned covariate vector $\dot{\mathbf{X}}_i = \mathbf{X}_i - \bar{\mathbf{X}}_i$ as an additive term and as an interaction with the treatment indicator.

[4] We will conduct the data analysis outlined in this section using the R programming language with the scripts included in Appendix C.

Table 1: Primary outcome variables

Variable	Description
Self-efficacy	
Affect	
Video selection	
Savings	

Table 2: Primary hypothesis tests

Null hypothesis	Description
$H_0 : \beta_1 = 0$	Effect of individual empowerment frame relative to poverty alleviation frame
$H_0 : \beta_2 = 0$	Effect of collective support frame relative to poverty alleviation frame
$H_0 : \beta_1 = \beta_2$	Effect of collective support frame relative to individual empowerment frame

$$Y_i = \beta_0 + \beta_1 \text{IND}_i + \beta_2 \text{COL}_i + \gamma_0 \dot{\mathbf{X}}_i' + \gamma_1 \text{IND}_i \dot{\mathbf{X}}_i' + \gamma_2 \text{COL}_i \dot{\mathbf{X}}_i' + \varepsilon_i \tag{2}$$

The set of indicators partitions our sample so that our estimate for β_j remains unbiased for the average treatment effect (Lin 2013). We will estimate cluster-robust standard errors at the individual level. We use this model to test the hypotheses detailed in Table 2 including the control variables listed in Table 3.

Table 3: Control variables for covariate adjustment

Variable	Description
Age	Dummy variable indicating participant is over 25
Gender	Dummy variable indicating participant is female
Employment	Dummy variable indicating participant is employed
Education	Dummy variable indicating participant completed std. 8
Children	Dummy variable indicating participant has children

4.2 Randomization inference

One potential concern is that inference might be invalidated by finite sample bias in estimates of the standard errors. To address this issue, we will conduct randomization inference to test the Fisherian sharp null hypothesis of no treatment effect for every participant (Fisher 1935).[5] We perform Monte Carlo approximations of the exact p-values using $M = 10,000$ permutations of the treatment assignment. We will then estimate our primary specification within each m^{th} permutation and calculate the standard Wald statistics for each of our hypothesis tests. We will compare the Wald statistics from the original sample with the distribution of permuted statistics to produce approximations of the exact p-values:

$$\hat{p}_\beta = \frac{1}{10,000} \sum_{m=1}^{10,000} \mathbf{1}\left[\hat{\beta}'_m V(\hat{\beta}_m)^{-1} \hat{\beta}_m \geq \hat{\beta}'_{obs.} V(\hat{\beta}_{obs.})^{-1} \hat{\beta}_{obs.}\right] \tag{3}$$

Following Young (2015), we will permute the data and calculate the regressions for all outcomes within each draw.

[5] Note that this is more restrictive than the null hypothesis of zero average treatment effect we will test in the previous section.

4.3 Heterogeneous treatment effects

We will analyze the extent to which the policy frames produced heterogeneous treatment effects with the following specification.

$$Y_i = \beta_0 + \beta_1 \textsc{Ind}_i + \beta_2 \textsc{Col}_i + \delta_0 x_i + \delta_1 \textsc{Ind}_i x_i + \delta_2 \textsc{Col}_i x_i + \varepsilon_i \tag{4}$$

x_i is the binary dimension of heterogeneity measured before treatment assignment. δ_1 and δ_2 identify the heterogeneous treatment effects of the individual empowerment and collective support frames relative to the poverty alleviation frame. Testing $\delta_1 = \delta_2$ identifies heterogeneous effects between the former two frames. Standard errors are clustered at the individual level. We estimate this model with the baseline variables summarized in Table 4.

Table 4: Dimensions of heterogeneity

Variable	Description
Age	Dummy variable indicating participant is over 25
Gender	Dummy variable indicating participant is female
Marital status	Dummy variable indicating participant is married or co-habitating 2
Education	Dummy variable indicating participant completed std. 8
Children	Dummy variable indicating participant has children

4.4 Multiple testing adjustment

Given that our survey instrument included several items related to a single behavior or dimension, we will calculate sharpened q-values over outcomes in Table 1 to control the false discovery rate (Benjamini, Krieger, and Yekutieli 2006). Rather than specifying a single q, we will report the minimum q-value at which each hypothesis is rejected (Anderson 2008). We will apply this correction separately for each hypothesis test and will report both standard p-values and minimum q-values in our analysis.

References

Anderson, Michael L. “Multiple Inference and Gender Differences in the Effects of Early Intervention: A Reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects”. In: *Journal of the American Statistical Association* 103.484 (2008), pp. 1481–1495. ISSN: 0162-1459. DOI: 10.1198/016214508000000841.

Benjamini, Yoav, Abba M. Krieger, and Daniel Yekutieli. “Adaptive Linear Step-up Procedures That Control the False Discovery Rate”. In: *Biometrika* (2006), pp. 491–507.

Fisher, Ronald Aylmer. *The Design of Experiments.* Includes index. Bibliography: p. 245. Edinburgh: Oliver & Boyd, 1935.

Haushofer, Johannes et al. *A Methodology for Laboratory Experiments in Developing Countries: Examples from the Busara Center.* SSRN Scholarly Paper ID 2155217. Rochester, NY: Social Science Research Network, Feb. 24, 2014.

Jack, William and Tavneet Suri. *Mobile money: The economics of M-PESA*. National Bureau of Economic Research, 2011.

Lin, Winston. “Agnostic notes on regression adjustments to experimental data: Reexamining Freedman’s critique”. In: *The Annals of Applied Statistics* 7.1 (Mar. 2013), pp. 295–318. ISSN: 1932-6157, 1941-7330. DOI: 10.1214/12-AOAS583.

Mbiti, Isaac and David N. Weil. *Mobile banking: The impact of M-Pesa in Kenya.* National Bureau of Economic Research, 2011.

Young, Alwyn. *Channeling Fisher: Randomization Tests and the Statistical Insignificance of Seemingly Significant Experimental Results.* Technical Report, Working paper, 2015.

A. Consent Form

B. Survey Instrument

C. Data Analysis Scripts

C.1 Packages

```
setwd("/Users/Justin/Google Drive/UBIF/UBIF_Deliverables/UBIF_PAP/K1_PAP") # make this r
set.seed(47269801)

required.packages <- c("dplyr", "multiwayvcov", "multcomp", "knitr")
packages.missing <- required.packages[!required.packages %in% installed.packages()[,"Pac

if(length(packages.missing) > 0) {install.packages(required.packages, repo="https://cran
lapply(required.packages, library, character.only = TRUE)
```

C.2 User-defined functions

```
## RegTest conducts asymptotic test from linear model ##

RegTest <- function(equation, clustvars, hypotheses, data) {

    model <- lm(equation, data = data, na.action = na.omit)

    if (missing(clustvars)) model$vcov <- vcov(model)
    else model$vcov <- cluster.vcov(model, cluster = clustvars)

    model$test <- summary(glht(model, linfct = hypotheses, vcov = model$vcov))$test

    numhyp <- length(hypotheses)

    EST <- matrix(nrow = numhyp, ncol = 4)

    for (i in 1:numhyp) {

        EST[i, 1] <- model$test$coefficients[i]
        EST[i, 2] <- model$test$tstat[i]
        EST[i, 3] <- model$test$sigma[i]
        EST[i, 4] <- model$test$pvalues[i]

    }

    colnames(EST) <- c("Estimate", "Tstat", "SE", "P")

    return(EST)

}

## PermTest returns MC approximations of the exact p-value ##
```

```
PermTest <- function(equation, treatvars, clustvars, hypotheses, iterations, data) {

    stopifnot(length(hypotheses) <= 1)

    obsEST <- RegTest(equation, clustvars, hypotheses, data)
    obsStat <- obsEST[1, 2]

    simEST <- matrix(ncol = 4)

    for (i in 1:iterations) {

        simTreat <- data[, treatvars, drop = FALSE]
        simTreat <- simTreat[sample(nrow(simTreat)),]

        simData <- cbind(simTreat, data[, !(names(data) %in% treatvars), drop = FALSE])
        colnames(simData)[1:2] <- treatvars

        simEST <- rbind(simEST, RegTest(equation, clustvars, hypotheses, data = simData

    }

    simSTAT <- simEST[2:nrow(simEST), 2]
    countSTAT <- matrix(abs(simSTAT) >= abs(obsStat), ncol = 1)

    ExactP <- matrix(1, nrow = 1, ncol = nrow(countSTAT)) %*% countSTAT
    ExactP <- ExactP / iterations

    EST <- cbind(obsEST, ExactP)

    colnames(EST) <- c("Estimate", "Tstat", "SE", "P", "ExactP")

    return(EST)

}

## FDR returns minimum q-values ##

FDR <- function(pvals) {

    return(pvals)

}
```

C.3 Data cleaning

```
## Create locals for simulation ##

  OBS <- 510
```

```r
## Generate treatment ##

  Treat <- sample(0:2,OBS, rep = TRUE, prob = c(.33, .33, 0.33)) %>%
  factor(levels = c(0, 1, 2), labels = c("Poverty", "Ind.", "Col."))

  Pov <- (Treat == "Poverty") * 1
  Ind <- (Treat == "Ind.") * 1
  Col <- (Treat == "Col.") * 1

## Generate gender ##

 Gen <- sample(0:1,OBS,rep = TRUE,prob = c(.5,.5))  %>%
  factor(levels = c(0,1), labels = c("Male","Female"))

## Generate factor variable measuring highest level of education ##

 Edu <- sample(1:3,OBS,rep = TRUE,prob = c(.5,.3,.2)) %>%
  factor(levels = c(1,2,3), labels = c("Primary school","High school","University & abov

## Generate income ##

 LnInc <- rnorm(OBS, mean = 5, sd = 1)
 Inc <- exp(LnInc)

## Generate y with notreatment effect ##

  yNull <- rnorm(OBS, 0, 1)

## Generate outcome with effects
  yInd <- (0.8 * Ind) + rnorm(OBS, 0, 1)
  yCol <- (0.4 * Col) + rnorm(OBS, 0, 1)

## Generate id ##

  ID <- matrix(1:OBS, ncol = 1)

## Create, save dataframe ##

  TestData <- data.frame(ID, Treat, Pov, Ind, Col, Gen, Edu, Inc, yNull, yInd, yCol)
```

C.4 Treatment effect

```r
hypotheses <- c("Ind = 0", "Col = 1", "Ind - Col = 0")
equations <- c("yNull ~ Ind + Col", "yInd ~ Ind + Col", "yCol ~ Ind + Col")

for (h in hypotheses) {

    RES <- matrix(nrow = 1, ncol = 5)
```

```
        for (eqn in equations) {

            # RES <- rbind(RES, RegTest(eqn, clustvars = TestData£ID, hypotheses = c(h), da
            RES <- rbind(RES, PermTest(eqn, treatvars = c("Treat"), clustvars = TestData$ID

        }

        RES <- RES[2:nrow(RES), 1:ncol(RES)]
        RES <- cbind(RES, FDR(RES[, 4]))

        rownames(RES) <- equations
        colnames(RES)[6] <- "Min. Q"

        print("-------------------------------------------------------------------", quote
        print(paste("H_0:", h), quote = FALSE)
        print(RES, quote = FALSE)
        print("-------------------------------------------------------------------", quote

    }

## [1] -------------------------------------------------------------------
## [1] H_0: Ind = 0
##                        Estimate      Tstat        SE            P ExactP
## yNull ~ Ind + Col  0.03075319  0.2795791 0.1099982 7.799145e-01      1
## yInd ~ Ind + Col   0.73884926  7.0165263 0.1053013 7.320589e-12      1
## yCol ~ Ind + Col  -0.23505753 -2.1757542 0.1080350 3.003476e-02      1
##                           Min. Q
## yNull ~ Ind + Col 7.799145e-01
## yInd ~ Ind + Col  7.320589e-12
## yCol ~ Ind + Col  3.003476e-02
## [1] -------------------------------------------------------------------
## [1] -------------------------------------------------------------------
## [1] H_0: Col = 1
##                       Estimate     Tstat        SE            P ExactP
## yNull ~ Ind + Col 0.09958245 -8.354382 0.1077779 6.661338e-16      1
## yInd ~ Ind + Col  0.05405943 -8.599148 0.1100040 0.000000e+00      1
## yCol ~ Ind + Col  0.46069496 -4.894362 0.1101890 1.327395e-06      1
##                           Min. Q
## yNull ~ Ind + Col 6.661338e-16
## yInd ~ Ind + Col  0.000000e+00
## yCol ~ Ind + Col  1.327395e-06
## [1] -------------------------------------------------------------------
## [1] -------------------------------------------------------------------
## [1] H_0: Ind - Col = 0
##                        Estimate      Tstat        SE            P ExactP
## yNull ~ Ind + Col -0.06882926 -0.6114888 0.1125601 5.411501e-01      1
## yInd ~ Ind + Col   0.68478983  6.1745265 0.1109056 1.361377e-09      1
## yCol ~ Ind + Col  -0.69575249 -6.2718404 0.1109327 7.649560e-10      1
##                           Min. Q
## yNull ~ Ind + Col 5.411501e-01
## yInd ~ Ind + Col  1.361377e-09
```

```
## yCol ~ Ind + Col  7.649560e-10
## [1] ---------------------------------------------------------------------
```

C.5 Covariate-adjustment

```
    hypotheses <- c("Ind = 0", "Col = 1", "Ind - Col = 0")
    equations <- c("yNull ~ Ind + Col + Gen + LnInc", "yInd ~ Ind + Col + Gen + LnInc", "yCo

    for (h in hypotheses) {

        RES <- matrix(nrow = 1, ncol = 5)

        for (eqn in equations) {

            # RES <- rbind(RES, RegTest(eqn, clustvars = TestData£ID, hypotheses = c(h), da
            RES <- rbind(RES, PermTest(eqn, treatvars = c("Treat"), clustvars = TestData$ID

        }

        RES <- RES[2:nrow(RES), 1:ncol(RES)]
        RES <- cbind(RES, FDR(RES[, 4]))

        rownames(RES) <- equations
        colnames(RES)[6] <- "Min. Q"

        print("---------------------------------------------------------------------", quote
        print(paste("H_0:", h), quote = FALSE)
        print(RES, quote = FALSE)
        print("---------------------------------------------------------------------", quote

    }

## [1] ---------------------------------------------------------------------
## [1] H_0: Ind = 0
##                                      Estimate      Tstat        SE
## yNull ~ Ind + Col + Gen + LnInc  0.02918267  0.2648791 0.1101735
## yInd ~ Ind + Col + Gen + LnInc   0.73587148  6.9894548 0.1052831
## yCol ~ Ind + Col + Gen + LnInc  -0.23740448 -2.1909366 0.1083575
##                                              P ExactP       Min. Q
## yNull ~ Ind + Col + Gen + LnInc 7.912107e-01      1 7.912107e-01
## yInd ~ Ind + Col + Gen + LnInc  8.768986e-12      1 8.768986e-12
## yCol ~ Ind + Col + Gen + LnInc  2.891262e-02      1 2.891262e-02
## [1] ---------------------------------------------------------------------
## [1] ---------------------------------------------------------------------
## [1] H_0: Col = 1
##                                    Estimate     Tstat        SE
## yNull ~ Ind + Col + Gen + LnInc 0.09762865 -8.358295 0.1079612
## yInd ~ Ind + Col + Gen + LnInc  0.05061641 -8.571130 0.1107653
## yCol ~ Ind + Col + Gen + LnInc  0.45972791 -4.916996 0.1098785
##                                              P ExactP       Min. Q
```

```
## yNull ~ Ind + Col + Gen + LnInc 6.661338e-16      1 6.661338e-16
## yInd ~ Ind + Col + Gen + LnInc  1.110223e-16      1 1.110223e-16
## yCol ~ Ind + Col + Gen + LnInc  1.190400e-06      1 1.190400e-06
## [1] --------------------------------------------------------------------
## [1] --------------------------------------------------------------------
## [1] H_0: Ind - Col = 0
##                                    Estimate      Tstat        SE
## yNull ~ Ind + Col + Gen + LnInc -0.06844599 -0.6068275 0.1127932
## yInd ~ Ind + Col + Gen + LnInc   0.68525507  6.1372269 0.1116555
## yCol ~ Ind + Col + Gen + LnInc  -0.69713239 -6.2877852 0.1108709
##                                            P ExactP      Min. Q
## yNull ~ Ind + Col + Gen + LnInc 5.442381e-01      1 5.442381e-01
## yInd ~ Ind + Col + Gen + LnInc  1.699181e-09      1 1.699181e-09
## yCol ~ Ind + Col + Gen + LnInc  6.975509e-10      1 6.975509e-10
## [1] --------------------------------------------------------------------
```

C.6 Heterogeneous treatment effects