This document describes plans to analyze data on the effects of various cash transfer designs collected by the NGO GiveDirectly as part of a collaboration with ideas42. We briefly describe key outcomes and specifications (including plans for inference) and samples. As the exercise was exploratory in nature and collected a large number of outcomes, we specify a few as “priority outcomes for each test but in general plan to examine effects on the full set.

1 Outcomes

We define the following key outcomes to which we then refer in what follows:

- Net assets (and its subcategories): from modules A, B, D, and E
- Net income (and its subcategories): from modules A and C
- Annualized expenditure including net transfers (and its subcategories): from modules E and F
- Retrospective transfer preference: H2
- Index of financial stresses: aggregating I1 and I2
- Index of progress towards goals made since transfer:
- Index of social input into decision-making: aggregating responses to K2, K9, K10, K16, and K17
- Index of deliberation in decision-making: aggregating responses to K1, K3, K4, K5, K6, K7, K8, K11, K12, K18
- Satisfaction with choices: R1
- Index of regret: aggregating R3 through R11
- Value attached to things purchased: R12

2 Average effects of treatment

2.1 Effects of tranche structure

We seek to estimate two quantities: the effect of receiving funds in 2 tranches as opposed to 1, and the effect of being assigned one’s preferred tranching structure. To calculate these we estimate

$$Y_i = \alpha + \beta_1 L_i(\tilde{L}_i) + \beta_2 L_i(1 - \tilde{L}_i) + \gamma \tilde{L}_i + \epsilon_i \qquad (1)$$

Here L_i ($\tilde{L}_i$) indicates whether recipient i was assigned to (preferred to) receive payment in a single lump sum, as opposed to two installments. Note that this design accounts for the fact that randomization was stratified on preferences, so that we do not cluster standard errors by preference. We estimate this model using the the 90% of subjects who were assigned to a tranche structure chosen at random (and thus were *not* assigned to have their preferred tranche structure implemented for sure). We then test

$$\rho^1\beta_1 + \rho^2\beta_2 = 0 \tag{2}$$
$$\rho^1\beta_1 - \rho^2\beta_2 = 0 \tag{3}$$

where ρ^p is the fraction of subjects preferring option p. The first test measures the average impact of getting two transfers as opposed to one; the second measures the average impact of getting your preferred tranche structure as opposed to not. We also estimate models that fully interact the right-hand side of (1) with the (discretized) baseline value of the dependent variable, and then calculate the average treatment effect as the weighted sum of the category-specific effects weighted by the size of each category.

When examining the impact of receiving 2 tranches as opposed to 1, our focus is on whether these structures lead to different uses of money and thus different aggregate patterns in household income statements and balance sheets, and also whether experiencing a given transfer structure affects recipients preferences. We prioritize the following outcomes:

- Net assets (and its subcategories)
- Net income (and its subcategories)
- Annualized expenditure including net transfers (and its subcategories)
- Retrospective transfer preferences
- Value attached to things purchased

When examining the impact of receiving ones preferred transfer structure, our focus is on understanding whether giving recipients control over transfer structure leads to outcomes that they prefer. We therefore prioritize the following outcomes:

- Index of financial stresses
- Index of social input into decision-making
- Index of deliberation in decision-making
- Satisfaction with choices
- Index of regret
- Value attached to things purchased
- Index of progress towards goals made since transfer

Within the subcategories noted above we will report both the usual standard errors and also p-values corrected to control the false discovery rate.

2.2 Effects of timing

First, we examine whether receiving money earlier / later leads to different uses and outcomes. We estimate

$$Y_i = \alpha + \beta_t T_i^a + \epsilon_i \tag{4}$$

where T_i^a is the average number of months delay from the scheduled start of payments overall to the date on which recipient i was assigned to be paid. For recipients who were assigned to receive a single tranche this is simply the month on which they were scheduled to be paid; for those assigned to receive two tranches it is the average of the two months on which they were scheduled to be paid (e.g. a recipient scheduled to receive payments in months 2 and 7 would have $T_i^a = \frac{2+7}{2} = 4.5$). We estimate this using the 90% of recipients who were assigned a timing at random, excluding the 10% who were given their preferred timing. We first estimate pooling those who received transfers in one and in two tranches, but also estimate for each sub-group separately. We cluster standard errors by recipients stated timing preferences (12 possibilities for single-tranche recipients and 6 for two-tranche recipients, for a total of 18 possible values) on which randomization was stratified. We will also estimate an analogous specification with a quadratic term in T_i^a to test for any non-linearities in the effect of timing.

When examining the impacts of transfer timing, our focus is on understanding (a) simple economic dynamics (e.g. does more recent receipt imply higher expenditure and lower asset accumulation), and (b) how the time lag between notification and receipt of transfer affects planning and decision-making. We therefore prioritize the following outcomes:

- Net assets (and its subcategories)
- Net income (and its subcategories)
- Annualized expenditure including net transfers (and its subcategories)
- Index of social input into decision-making
- Index of deliberation in decision-making
- Value attached to things purchased

Second, we examine whether getting money at the time the recipient wanted it led to different subjective satisfaction with the results. Conceptually, we wish to estimate

$$Y_i = \alpha + \beta 1(|T_i^a - T_i^p| < \kappa) + \epsilon_i \tag{5}$$

As above, T_i^a is the (randomly assigned) date on which subject i was scheduled to receive their average dollar, while T_i^p the date on which they preferred to receive it. κ is a tuning parameter which determines what constitutes a "match; we define $\kappa = 1$ initially but will also explore sensitivity to looser definitions. Note, however, that β in (5) is experimentally identified only conditional on T_i^p, which is endogenous. We therefore fully interact (5) and report the (bin-size weighted) average value of β across all values of T_i^p as the statistic of interest. As with tranching preferences, our primary interest in exploring the effects of timing structure is to understand whether giving recipients control over transfer structure leads to outcomes that they prefer. We therefore prioritize the following outcomes:

- Index of financial stresses
- Index of social input into decision-making
- Index of deliberation in decision-making
- Satisfaction with own money use choices
- Index of regret
- Value attached to things purchased
- Index of progress towards goals made since transfer

2.3 Effects of information treatments

Conceptually, we think of the probability that individual i invested in asset a as a function of the difference between their priors about that asset and any information they are experimentally assigned to receive:

$$Y_{ia} = \alpha_a + \delta_a I_i^p + \beta_p I_{ia}^p * (\hat{P}_a - \tilde{P}_{ia}) + \beta_r I_{ia}^r * (\hat{R}_a - \tilde{R}_{ia}) \\ + \gamma_p \tilde{P}_{ia} + \gamma_r \tilde{R}_{ia} + \phi_p I_{ia}^p \tilde{P}_{ia} + \phi_r I_{ia}^r \tilde{R}_{ia} + \epsilon_{ia} \quad (6)$$

Here y_{ia} indicates whether individual purchased asset a; I_i^p indicates whether the individual was given information about popularity (as opposed to information about returns); I_{ia}^p (I_{ia}^r) indicates whether individual i was given information about the popularity of (returns on) investment a; $\hat{P}_a$ is the popularity score communicated to individuals who were given the popularity treatment, $\tilde{P}_{ia}$ is the individuals self-reported prior about that score, and $\hat{R}_a - \tilde{R}_{ia}$ is analogously the difference between the individuals priors and the message delivered about net returns. Intuitively, this models behavior as a function of the surprise contained in any information delivered (as opposed to the delivery of information per se). The remaining variables condition on priors and the interaction between priors and treatment, so that identification of the parameters () of interest is driven purely by experimental assignment.

We estimate this relationship using the full sample of households. We first estimate it pooling all five investments a and multi-way clustering standard errors at the individual and stratum level (as randomization was stratified on predicted probability of being subsequently found ineligible). We then estimate it separately for each investment, in this case clustering standard errors by stratum and reporting both the usual standard errors and also p-values corrected to control the False Discovery Rate (FDR) within the group of 5 investments.

For each estimation, we estimate both (1) and a model that fully interacts this specification with a categorical variable from the baseline survey indicating the individuals prior stated likelihood of making investment a. This variables take on values 0 (no plans to invest), 1 (low priority), or 2 (high priority). We do not pre-specify plans to condition on prior ownership of these assets as ownership of any of the five is uncommon in our baseline.

As a robustness check, we will also examine whether results from probit estimation of these models are meaningfully different.

We are also interested in the impacts of information treatments on the decision-making process itself. To examine this we estimate

$$Y_i = \alpha + \beta_p I_i^p + \epsilon_{ia} \tag{7}$$

where Y_i is an outcome characterizing the decision-making process and I_i^p indicates whether individual i received information about popularity (since all individuals received information either about popularity or about returns, the implicit "control" in this specification are the latter). In this specification, β_p measures the effect of being given popularity information as opposed to returns information. Our outcomes of interest here are

- Index of social input into decision-making
- Index of deliberation in decision-making

2.4 Effects of "ready cash"

Finally, we examine whether recipients' outcomes were affected by the timing of the "ready cash" they were given prior to expressing their preferences over transfer structure. We estimate

$$Y_i = \alpha + \beta_L L_i + \epsilon_{ia} \tag{8}$$

Here L_i indicates whether the individual received their ready cash at a later date, immediately before expressing their preferences; β_L is thus the effect of having recently received a small amount of cash. We focus on whether this affected how the recipient made decisions about using the transfer as well as their ultimate satisfaction with the results:

- Index of social input into decision-making
- Index of deliberation in decision-making
- Satisfaction with own money use choices
- Index of regret
- Value attached to things purchased
- Index of progress towards goals made since transfer

3 Attrition

We will test whether attrition from the endline survey was differential with respect to treatment status. If so, we will additionally report Lee bounds for the parameters described above.

4 Interaction between treatments

We do not pre-specify any analysis of interactions between the various treatments, as the study was designed to be powered for main effects only. We may conduct such analysis ex post and treat it as exploratory.

5 Heterogeneous effects

We do not pre-specify generic hypotheses about heterogeneity of treatment effects other than those described above, e.g. that the impact of information may depend on priors. We may conduct a range of exploratory analyses, e.g. splitting the sample by measures of cognitive ability or using data-driven techniques such as those described in Athey & Wager (2017), "Estimation and Inference of Heterogeneous Treatment Effects using Random Forests."