Charitable giving by the poor. A field experiment
- Project details -

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1. Power calculations

We calculated power in our experiment using rdpower package for stata. Given our cluster randomization, we first need an estimate of intra cluster correlation (ICC). We are not aware of any study in a similar setting that could give us a valid estimate of ICC. Most studies on charitable giving rely on simple randomization and are conducted in western countries with middle-income subjects. In order to obtain best guess we computed ICC in our sample with respect to the current balance (current debt of a client) and total current credit issued per client. ICC based on current balance equals to 0.02 while ICC based on credit issued equals to 0.04. Assuming ICC=0.02, with 52 clusters and (over) 1500 individuals per cluster, we have enough power (>0.8) to detect effect size of 0.1. While assuming ICC=0.04, there is enough power to detect effect size of 0.12. Note however, that there is additional efficiency gain due to blocked randomization (see below) and potential inclusion of covariates when estimating the causal effect.

2. Randomization and balance

We performed blocked randomization using blockTools command in R (Moore and Schnakenberg 2016). The randomization was conducted at the office level taking into account the following variables: number of credit specialists working for the office, average interest rate of all current credits, average current balance of all current credits, average cycle (number of credits issued to a current credit holder), average share of credit repayments delayed by 30 days, average experience of credit specialists in months, share of female credit specialists, average age of clients, share of female clients, share of clients married, share of clients of Kyrgyz nationality, region dummy 1-8, dummy equal to one if the current realized charitable project by the microlending company is in the same place as the office, share of clients of Uzbek nationality, and average number of children per client with the following weights: 10, 2, 2, 12, 3, 15, 2, 1, 1, 2, 1, 1, 4, 4, 4, 4, 4, 4, 4, 9, 4, 2. The choice of the variables and weights was motivated by the perceived importance of a particular variable, and in some cases, by the convergence properties of the algorithm. The client level data is as of 16.01.2018 but the specialists level data is as of the summer 2017. The sample has been divided block wise in 4 groups with earlier blocks being more homogenous than later ones. The total number of blocks is 26 (we dropped block 27 with only one office that was very different from others) making a total of 104 office level treatment units. We combined the groups 1-2 and 3-4 for the treatments A (no local benefits) and B (local benefits) and groups 1, 3 and 2, 4 for the treatments C (no matching) and D (matching). Thus group one was chosen to be a baseline, group two had the matching only, group 3 had the local benefits only, and group 4 had both matching and local benefits.

<u>Office level data</u>: In order to test the balance, we run a set of pairwise t-tests for comparisons between A and B, and between C and D. Given that the blocked randomization was performed at the office level (104 offices), there is a good balance concerning all available variables as can be seen in Table 1. There is no t-test p-value <10%.

Table 1: Balance at the office level

	meanA	seA	meanB	seB	p-value	meanC	seC	meanD	seD	p-value
nspecialists	3.74	0.26	3.58	0.27	0.67	3.36	0.24	3.96	0.28	0.11
nsfemale	2.18	0.25	2.07	0.25	0.76	1.99	0.21	2.26	0.29	0.45
nsclients	1362.96	115.92	1297.72	101.12	0.67	1213.27	95.11	1451.90	119.98	0.12
snat_kg	0.88	0.04	0.89	0.04	0.85	0.87	0.04	0.91	0.04	0.48
snat_uzb	0.10	0.04	0.09	0.04	0.80	0.12	0.04	0.07	0.03	0.34
snat_tdj	0.01	0.01	0.01	0.01	0.75	0.00	0.00	0.02	0.01	0.17
snat_other	0.01	0.01	0.01	0.01	0.92	0.01	0.01	0.00	0.00	0.45
lang_kg	0.88	0.04	0.89	0.04	0.85	0.87	0.04	0.91	0.04	0.48
lang_uzb	0.10	0.04	0.09	0.04	0.80	0.12	0.04	0.07	0.03	0.34
lang_ru	0.01	0.01	0.02	0.01	0.84	0.01	0.01	0.02	0.01	0.48
sage	30.63	0.56	31.04	0.70	0.66	30.74	0.60	30.92	0.67	0.84
experience_month	38.46	2.58	35.96	2.66	0.50	35.66	2.28	38.76	2.92	0.40
mclients	359.08	11.36	352.49	11.62	0.69	353.44	11.28	358.37	11.71	0.76
par30	0.60	0.12	0.92	0.24	0.24	0.64	0.20	0.87	0.18	0.39
portfolio	9561462.30	343694.31	9500509.93	318451.34	0.90	9453518.64	321921.28	9611972.26	342339.52	0.74
region_code	4.84	0.28	4.70	0.31	0.74	4.82	0.28	4.72	0.31	0.81
nclients	1696.12	151.04	1495.00	121.65	0.30	1459.24	124.68	1731.88	147.38	0.16

nfemale	980.40	87.49	868.16	76.34	0.34	829.92	74.66	1018.64	87.60	0.10
mfemale	0.57	0.01	0.58	0.01	0.74	0.57	0.01	0.58	0.01	0.71
Dummy_married	0.70	0.01	0.69	0.02	0.51	0.69	0.02	0.69	0.01	0.99
Dummy_single	0.13	0.01	0.13	0.01	0.84	0.13	0.01	0.13	0.01	0.77
interest	31.05	0.26	31.30	0.33	0.54	31.42	0.30	30.93	0.28	0.24
Dummy_kg_nat	0.79	0.04	0.83	0.04	0.45	0.78	0.04	0.84	0.03	0.32
Dummy_uzb_nat	0.17	0.04	0.13	0.03	0.44	0.17	0.04	0.12	0.03	0.37
Dummy_tadj_nat	0.01	0.00	0.02	0.01	0.47	0.01	0.01	0.01	0.01	0.79
Dummy_rus_nat	0.01	0.00	0.01	0.00	0.58	0.01	0.00	0.01	0.00	0.49
Dummy_other_nat	0.02	0.01	0.02	0.00	0.32	0.02	0.01	0.02	0.00	0.30
Dummy_new_client	0.38	0.01	0.37	0.01	0.68	0.37	0.01	0.37	0.01	0.91
age	41.59	0.28	41.79	0.31	0.64	41.65	0.30	41.74	0.29	0.83
Kids	1.61	0.04	1.67	0.05	0.34	1.63	0.04	1.65	0.05	0.75
Family_size	4.38	0.06	4.31	0.07	0.47	4.36	0.06	4.32	0.06	0.68
Current_balance	27077.33	481.98	27219.52	671.89	0.86	26803.92	652.24	27492.94	503.68	0.41
Sum_issued	43301.47	777.96	43868.83	878.73	0.63	43430.35	801.53	43739.95	858.63	0.79
Cycle	2.87	0.09	2.92	0.08	0.70	2.82	0.07	2.98	0.09	0.17
delayed	0.03	0.00	0.03	0.01	0.44	0.03	0.01	0.03	0.00	0.63
region_dummy1	0.04	0.03	0.06	0.03	0.65	0.02	0.02	0.08	0.04	0.17
region_dummy2	0.04	0.03	0.04	0.03	0.94	0.04	0.03	0.04	0.03	0.94
region_dummy3	0.26	0.06	0.22	0.06	0.63	0.26	0.06	0.22	0.06	0.68
region_dummy4	0.18	0.05	0.24	0.06	0.47	0.26	0.06	0.16	0.05	0.22
region_dummy5	0.12	0.05	0.06	0.03	0.30	0.10	0.04	0.08	0.04	0.73
region_dummy6	0.10	0.04	0.14	0.05	0.54	0.08	0.04	0.16	0.05	0.22
region_dummy7	0.16	0.05	0.10	0.04	0.36	0.12	0.05	0.14	0.05	0.79
region_dummy8	0.06	0.03	0.08	0.04	0.70	0.06	0.03	0.08	0.04	0.70
region_dummy9	0.04	0.03	0.06	0.03	0.65	0.06	0.03	0.04	0.03	0.65
sharefemalesp	0.56	0.05	0.55	0.05	0.91	0.58	0.05	0.54	0.05	0.56
projectproximity	0.10	0.04	0.08	0.04	0.72	0.10	0.04	0.08	0.04	0.73

Note: The base for all variables concerning credit specialist and clients are means at the office level

Table 2: Balance at the credit specialists' level

	meanA	seA	meanB	seB	p-value	meanC	seC	meanD	seD	p-value
region_dummy1	0.06	0.02	0.08	0.02	0.34	0.03	0.01	0.11	0.02	0.00
region_dummy2	0.05	0.02	0.03	0.01	0.38	0.04	0.02	0.04	0.01	0.67
region_dummy3	0.29	0.03	0.22	0.03	0.13	0.29	0.03	0.23	0.03	0.17
region_dummy4	0.14	0.03	0.29	0.03	0.00	0.27	0.03	0.16	0.03	0.01
region_dummy5	0.10	0.02	0.06	0.02	0.11	0.08	0.02	0.08	0.02	0.88
region_dummy6	0.08	0.02	0.14	0.03	0.09	0.06	0.02	0.15	0.03	0.01
region_dummy7	0.15	0.03	0.08	0.02	0.05	0.11	0.02	0.12	0.02	0.82
region_dummy8	0.09	0.02	0.05	0.02	0.19	0.07	0.02	0.07	0.02	0.82
region_dummy9	0.05	0.02	0.05	0.02	0.89	0.05	0.02	0.05	0.01	0.94
nat_kg	0.85	0.03	0.89	0.02	0.25	0.87	0.03	0.87	0.02	0.82
nat_uzb	0.13	0.02	0.09	0.02	0.21	0.11	0.02	0.11	0.02	0.99
nat_tdj	0.01	0.01	0.01	0.01	0.53	0.00	0.00	0.02	0.01	0.08
nat_other	0.01	0.01	0.01	0.01	0.60	0.01	0.01	0.01	0.01	0.49
lang_kg	0.85	0.03	0.89	0.02	0.25	0.87	0.03	0.87	0.02	0.82
lang_uzb	0.13	0.02	0.09	0.02	0.21	0.11	0.02	0.11	0.02	0.99
lang_ru	0.02	0.01	0.02	0.01	0.93	0.01	0.01	0.02	0.01	0.52
female	0.58	0.04	0.59	0.04	0.95	0.59	0.04	0.58	0.04	0.77
age	31.51	0.50	31.14	0.59	0.63	30.78	0.53	31.80	0.55	0.18
experience_month	41.90	2.09	38.85	2.24	0.32	37.25	2.01	43.17	2.24	0.05
clients	364.43	13.21	350.53	13.17	0.46	355.99	13.89	359.23	12.61	0.86
par30	0.60	0.09	1.00	0.22	0.08	0.71	0.15	0.86	0.16	0.50
portfolio	9757832.30	358254.42	9543717.16	362306.10	0.67	9584149.58	381037.86	9715301.27	342537.19	0.80
projectproximity	0.11	0.02	0.06	0.02	0.08	0.09	0.02	0.08	0.02	0.67

<u>Credit specialist data</u>: From a total of 492[1] we have individual level data on 370 credit specialists concerning their gender, region of origin, first language, age, experience in months etc. In what follows we check again balance of our treatment assignment based on the available characteristics using pairwise t-tests. In 56 comparisons, we find some significant differences (2 at $p<0.01$, 2 at $p<0.05$, and 6 at $p<0.1$), however, this approach is very conservative and might suffer from multiple testing problem. Therefore, in the next step, we run logit regressions with dependent variables being either treatment B or treatment D and all available individual level

[1] Excluding the dropped office.

variables as independent variables. Table 3 presents average marginal effects after logit. The robust standard errors are clustered at the office level. When looking at Table 4, we can assess which individual characteristics of clients are correlated with the probability of being assigned to a particular treatment. There are no significant correlations at all. We conclude that we have achieved a reasonable balance at the specialists' level.

Table 3: Credit specialist's characteristics and the probability of assignment to a treatment.

Dependent variable	Dummy treatment B	Dummy treatment D
(mean)	0.078	0.352
region_dummy1	(0.340)	(0.332)
(mean)	-0.136	-0.085
region_dummy2	(0.363)	(0.333)
(mean)	-0.036	-0.082
region_dummy3	(0.257)	(0.229)
(mean)	0.184	-0.131
region_dummy4	(0.254)	(0.233)
(mean)	-0.146	0.052
region_dummy5	(0.291)	(0.257)
(mean)	0.135	0.219
region_dummy6	(0.268)	(0.242)
(mean)	-0.097	0.005
region_dummy7	(0.271)	(0.256)
(mean)	-0.118	0.036
region_dummy8	(0.316)	(0.298)
nat_KG	-0.124	-0.051
	(0.237)	(0.252)
nat_uzb	-0.166	0.041
	(0.256)	(0.270)
female	0.033	-0.050
	(0.060)	(0.061)
age	0.001	0.000
	(0.004)	(0.004)
experience_month	-0.002	0.001
	(0.001)	(0.001)
clients	-0.000	0.000
	(0.001)	(0.001)
par30	0.012	0.012
	(0.016)	(0.016)
portfolio	0.000	-0.000
	(0.000)	(0.000)
(mean)	-0.132	-0.067
projectproximity	(0.165)	(0.163)
Observations	365	365
Pseudo R^2	0.062	0.062

Average marginal effects after logit, Robust standard errors clustered at office level in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Individual characteristics and the probability of assignment to a particular treatment.

Dependent variable	Dummy treatment B	Dummy treatment D
Cycle	-0.001	0.012^{***}
	(0.005)	(0.005)
issue_fee	0.004	-0.003
	(0.006)	(0.006)
Interest_rate	0.000	-0.002^{*}
	(0.001)	(0.001)
Current_balance	0.000	-0.000
	(0.000)	(0.000)
age	0.000	-0.000
	(0.001)	(0.001)
Dummy_kg_nat	0.052	0.092
	(0.082)	(0.085)
Dummy_uzb_nat	-0.020	0.056
	(0.117)	(0.119)
Dummy_tadj_nat	0.213	0.179
	(0.210)	(0.216)
Dummy_rus_nat	0.004	0.057
	(0.083)	(0.087)
Dummy_new_client	-0.006	0.008
	(0.019)	(0.020)
Kids	0.013	0.016
	(0.011)	(0.012)
Family_size	-0.004	-0.009
	(0.006)	(0.007)
Female	-0.007	0.005
	(0.009)	(0.009)
Dummy_married	-0.036^{*}	-0.017
	(0.020)	(0.022)
Dummy_single	-0.025	-0.002
	(0.029)	(0.032)
projectproximity	-0.141	-0.080
	(0.176)	(0.181)
Observations	161759	161759
Pseudo R^2	0.009	0.008

Average marginal effects after logit, Robust standard errors clustered at office level in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Individual level data: Given a large number of individuals (over 160,000) even small differences yield significant according to a simple t-test comparisons. Therefore, in order to assess the balance at clients level, we run logit regressions with dependent variables being either treatment B or treatment D and all available individual level characteristics as independent variables. Table

4 presents average marginal effects after logit. The robust standard errors are clustered at the office level. When looking at Table 4, we can assess which individual characteristics of clients are correlated with the probability of being assigned to a particular treatment. We find one coefficient significant at $p<0.01$ and two coefficients significant at $p<0.1$ but the size of the marginal effects is rather small in all cases. Given some potential imbalances, the robustness checks after our main analysis will include control variables.

3. Hypotheses

<u>Credit specialists:</u>

- (no treatment effect on credit specialists' motivation to ask clients for donations) We expect no treatment differences in shares of clients informed about the fundraising campaign

- (credit specialists' motivation effect) we expect motivated officers (with higher shares of informed clients) to raise more funds (even after accounting for higher shares)

<u>Clients:</u>

- (matching) we expect the response rate to be higher in the matching treatment than in control. We do not expect any change in the amount given (conditional on giving). We expect the combined effect (return from campaign) to be higher in the matching treatment. Explanation: Based on our previous research (for example, Huck and Rasul 2011; Huck, Rasul, and Shephard 2015; Adena and Huck 2017) we expect matching to crowd in small donations and crowd out large ones. Since our sample consists of low income individuals, we expect only the first effect to hold, inducing a larger response rate with all donation values being small.

- (local benefits) we expect local benefits to increase giving on the intensive margin. We expect nonnegative effect on the extensive margin. The combined effect (return) is expected to be positive in the local benefits treatment.

4. Analysis plan

We are going to analyze the following outcome variables:

- Donation dummy at the client level
- Amount given at the client level (including and excluding zeros)
- Share of individuals informed about the campaign by credit specialist based on a phone survey of a subsample of clients

For a descriptive part of our study, we are going to look at patterns of giving among the poor:

- Overall response rate, average positive donation, the combination of both (return from the campaign).
- How does the giving depend on gender, account balance and cycle, income (if available to us), proximity to a project realized, large city versus rural etc.?

For the main analysis, we'll be interested in the effect of treatments on our outcome variables. First, we are going to test whether treatments have any effect on the behavior of credit specialists. This, we are going to test by comparing the shares of clients informed by treatment. In case we do not reject the no-effect on credit specialists' hypothesis, we will proceed with the comparison of the donative behavior of clients by treatment. In case we do reject the no-effect on credit specialists' hypothesis, we will disentangle the total effect of treatments in the effect on credit specialists and on clients.

Methods:

- Comparisons of simple averages per treatment using appropriate parametric an dnon-parametric tests
- Regressions with dependent variable being donation dummy (probit, logit or rare events logit in case of a very low response rate), positive donations (OLS and areg absorbing loan officer id), donations including zeros (OLS and tobit), and share of clients informed on treatment dummies and control variables. In the case of very skewed distribution of donation values, the donation will be log transformed. Errors

will be clustered at the office level. He reason for the inclusion of controls is to increase power and correct for any potential imbalance, as well as for robustness.

Heterogeneity: We will study potential heterogeneity of treatment effect with respect to the gender of credit specialists, the proximity to a project implemented, the length of the relationship between a client and a credit specialist as proxied by the variable cycle, the experience of the specialists, the share of clients informed by a specialist (as a proxy for endeavor), income (if available), region, urban/rural status.

Other variables: In addition to any of the above specified variables, we will collect the missing credit specialist data. We will also make an attempt to receive (self-reported) income data on the clients' level. If possible, all baseline characteristics will be updated to match the time of the start of the experiment.

5. References

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