Is It Who You Are or What You Get? Comparing the Impacts of Loans and Grants for Microenterprise Development*

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Abstract

Is the type of financial support provided to businesses more important than which businesses receive it? Loans and grants can lead to differences in optimal investments and in scope for moral hazard. We randomize 3,294 business-loan applicants into receiving a loan, cash grant, in-kind grant or nothing. All treatments equally increase income, yet there are large differences *within* a treatment group with impacts concentrated at the top of the distribution. Those who succeed with loans are observationally equivalent to those who succeed with grants, showcasing that owner heterogeneity is more important than the type of support received in microenterprise development.

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1 Introduction

The return to capital in developing countries has been shown to be high (De Mel et al., 2008; McKenzie, 2015; Blattman and Ralston, 2015), but extending credit to enterprises has often had modest impacts on firm outcomes (Banerjee et al., 2015b). Are these seemingly conflicting pieces of evidence due to the different contexts and populations of these studies or due to the difference in optimal behavior when receiving an unrestricted capital grant relative to the more rigid structure of the credit products that have been tested? Earlier work has shown that flexible microcredit contracts can increase firm growth (Field et al., 2013; Barboni and Agarwal, 2018) while other papers show how individual characteristics like experience or optimism can be important determinants of the returns to capital (Banerjee et al., 2019a; Bryan et al., 2021). We provide evidence that individual heterogeneity is at least as important as contract type in microenterprise development.

Finding the most effective ways to improve microenterprise development is a priority for policymakers, academics and practitioners around the world and capital support is a commonly used tool. Economic theory provides ambiguous predictions about the impacts of different types of capital assistance on firm performance. While a cash grant is the most liquid, and hence easiest to allocate towards the highest return activity for the recipient, it is also the easiest to allocate to non-income generating activities that could increase consumption at the expense of the business. This may be due to a lack of self-control or family pressure to share the funds (Fafchamps et al., 2014), but also due to the income effect of an unconditional cash grant on labor supply (Banerjee et al., 2017). In-kind grants have the potential to mitigate these concerns due to the costs of liquidating the assets, but it also makes it more difficult for businesses to pivot to higher return opportunities that may arise. Standard loans have several drawbacks too, including needing to pay back the capital with interest, in our case on a monthly basis over 12 months. This potentially limits investment choice to things that have short-run and low-risk returns (Field et al., 2013). On the other hand, some make the case that forcing businesses to make monthly payments on a loan leads them to develop important discipline that improves the businesses' ability to be streamlined and efficient (Armendáriz and Morduch, 2010).

We ran an experiment with 3,294 individuals who applied for a loan to start a new business, or to grow an existing one, in Egypt. Conditional on being approved for the loan, we randomize individuals into one of four groups: a group that receives the (subsidized) loan they applied for, a group that receives the amount of the loan as a cash grant, a group that receives the items that they listed on their loan application as an in-kind grant, and a control group that receives no capital support. By randomizing *after* loan approval we are able to keep the selection of individuals constant across groups, allowing us to identify how the different contract types affect enterprise performance.

We focus on three main results. (1) Sixteen months after randomization all three forms of capital assistance lead to large increases in business assets and profits, particularly for women. Much of this impact is coming at the extensive margin through the creation of new businesses, and the impacts for loans and grants are all positive. This showcases that all three types of capital assistance can perform well in contexts where the return to capital is high and credit constraints bind. (2) While in-kind grants substantially outperform cash grants and microloans in increasing business profits, cash grants and loans have a positive impact on wage employment. This compensating effect leads to finding no significant differences between the three capital assistance treatments on total income (although total income for each group is still much higher than income in the control group). This provides evidence that unconditional cash grants can be just as effective as more restrictive options in encouraging work. (3) Using quantile regressions we document that the impacts on total income are concentrated at the top of the distribution for those that received a loan, consistent with the findings of Meager (2020), but we also show that cash and in-kind grants have the same pattern. Furthermore, we show that while the difference *within* a treatment arm is large there is no detectable difference *across* treatment arms at the same quantile, and that the baseline characteristics of top performers are statistically equivalent across groups. This provides evidence that "who you are" is more important than "what you get" in terms of increasing incomes using capital assistance.[1]

Digging deeper into these results we find that the in-kind grant had the largest impact on having a business. Only 15% of women in the control group have a business one year later, whereas 39% who received an in-kind grant have a business, a 24 percentage point increase

[1] Of course "who you are" is used here as a simplifying idiom. Individual characteristics are a poor proxy for describing a group of people, and those characteristics do not reflect the variety of societal challenges that face different individuals. People at the top of the distribution may succeed because they face less discrimination, not because they are necessarily more capable. Breaking these mechanisms down further are beyond the scope of this paper.

(a 158% increase relative to control). This results in an increase in average monthly business profits of 133 Egyptian Pounds (PPP Conversion Factor$\sim$3.25; 1USD$\sim$15EGP) relative to a control group average of 59EGP (a 225% increase). The business impacts for microloans and cash are also large and statistically significant relative to control, but lower than that of the in-kind grant. Impacts on men are also large, with a significant average increase in having a business of 14 percentage points (relative to 27% of control), and monthly business profits increasing by 100EGP (relative to 511 in control), but profits are imprecisely estimated and not statistically significant.

The impact on total income paints a more nuanced picture. Women who received the microloan and cash grant make up for their lower levels of business profits with higher levels of income from wage work. This leads to large and significant increases in total monthly income for women, averaging 132EGP relative to 459 in control (a 29% increase), but there is no statistically significant difference in total income across the three interventions. For men the increase in business profits across all three types of capital assistance is partially offset with decreases in income from wage earning activities, leading to relatively small increases in total monthly income that are not statistically different from the control group (average income for men in treatment is 2.5% more than control). We are able to further explore these differences with time-use data. Participation in the program leads to a significant increase in time spent in self-employment but it leads women to switch out of uncompensated chores and childcare activities and men to switch out of wage activities.

Turning to our third main result- using quantile regressions we find that the impacts of the microloans are concentrated at the top of the distribution, consistent with much of the earlier literature and summarized and analyzed in depth in Meager (2020). Expanding beyond this we show that cash and in-kind grants exhibit the same pattern with impacts concentrated at the top and no effect on the bottom of the distribution. Moreover, we reject equality of quantile treatment effects within a treatment arm, proving that there is significant heterogeneity in the impacts of each type of capital assistance. While there might be forms of heterogeneity that they fail to detect, this test for treatment effect heterogeneity can outperform more standard methods used in the literature like sub-group analysis and can be implemented easily across contexts. Moreover, when we compare impacts across treatments but at the same quantile (e.g. the quantile treatment effect of loans for people at the 90th quantile vs the quantile treatment effect of cash for people at the 90th quantile, etc) we cannot reject equality. We also provide evidence that the people at the top of the distribution across groups are similar, but that there are differences in characteristics between those at the top and the bottom of the distribution. This implies that there is a set of people who would succeed no matter what kind of support they received, i.e. that "who you are" is more important than "what you get".

We run three different kinds of tests to assess whether or not the characteristics of those at the top of the distribution are equal across groups. In our preferred test we compare a large set of baseline characteristics for individuals who are in the top 25% of income in the endline survey in each of the treatment groups and find that they are statistically balanced. We also implement standard tests for heterogeneity by baseline characteristics and more recent machine learning strategies developed in Chernozhukov et al. (2020) whose results are consistent with the existence of a stable group of applicants who succeed across interventions. Together we take these results as evidence that individual heterogeneity can be more important than the type of capital support received. This is true even in our sample where individuals were pre-screened on both their interest in getting a loan and submitting an acceptable business plan, limiting the potential individual heterogeneity we could observe.

These results have important implications for academics, policymakers and practitioners. First, while the earliest studies showed limited impacts of microcredit, we show that microcredit could have large positive impacts in a context where credit constraints bind and women struggle to find formal employment.[2] Second, learning to identify high-potential recipients is of first order importance, as we find large differences by recipient type but no differences by capital support type. Third, while in-kind grants improve business outcomes, more flexible funding increases wage work, providing further evidence that transfers to the poor do not lead to negative labor supply responses. Finally, we show that while loans are the most cost-effective way to generate employment, grants are equally cost-effective in generating income. Optimal policy will depend on the outcomes policymakers are looking to maximize.

We contribute to several strands of the literature including the above mentioned work on the returns to credit (Banerjee et al., 2015b; Meager, 2020) and the returns to grants

[2]More recent work has shown how microcredit can have positive impacts in the right context including Burke et al. (2019).

(De Mel et al., 2012; Fafchamps et al., 2014). By comparing loans and grants in the same context we are able to confirm results of previous work on microcredit, while deepening our understanding of how those results are linked to the literature on cash transfers. Two important papers also consider the impacts of loans and grants in the same context. Beaman et al. (2020) compares the return to grants for individuals who have applied for a loan to those who have not and find that applicants are positively selected. We expand on this work by comparing the returns to loans and grants for individuals with the same selection (all have applied for a loan), allowing for estimating the impacts of the contract structure itself. Fiala (2018) implements a 2x2 design of microloans or cash grants crossed with business training and compares those four groups to a control group. We extend on this work by focusing only on different types of capital support and achieving a higher powered test through a larger sample and higher take up.

We also contribute to the literature associated with the labor market impacts of unconditional cash transfers and universal basic incomes. Banerjee et al. (2019b) reviews this literature and notes while targeted programs (like in-kind grants) could more efficiently achieve certain goals (like increasing business income), they might do so at the expense of helping the poor address their individual needs (maybe some people could increase income better if they spent the money on training for employment). In our case, we show that women who were credit constrained used the flexible funds to increase income in both self-employment and working for others, while those who were provided the in-kind grant only increased income in self-employment. While we naturally expect capital constraints to affect business outcomes, it is less obvious why capital support would lead to an increase in women's wage work. We posit two potential explanations. First, is through information frictions. It is possible that receiving flexible capital induces women to engage with the market more, and through that process they learn about employment opportunities that are a better fit for them instead of working only on their own business. Second, is through family dynamics. It is possible that by receiving capital their families now consider them to be "economically active" which provides them more flexibility to work in any capacity relative to those in the control group whose families are more restrictive on what type of work is appropriate. Unfortunately, we do not have the data to differentiate between these two potential mechanisms.

We also contribute to the literature on supporting youth employment. Helping young people increase their economic activity is difficult, as shown in several meta-analysis of hundreds of studies of active labor market interventions (Card et al., 2018; McKenzie, 2017). There have been several studies examining the impacts of providing capital and/or training to increase employment among youth (Blattman et al., 2014, 2020, 2019; Berge et al., 2015; Baird et al., 2018; Brudevold-Newman et al., 2017) but there are no studies that examine the relative effectiveness of loans versus grants for increasing youth employment.

Finally, this paper makes a contribution to the literature on gender and development. Many papers find that returns to capital assistance for men outpace returns for women which are normally indistinguishable from zero.[3] We find large positive impacts of all types of capital assistance for women. Jayachandran (2019) outlines how social norms can act as a barrier to women's employment and discusses how women's business potential may be limited by intrahousehold dynamics. Several papers provide evidence for this hypothesis including Bernhardt et al. (2019) Fiala et al. (2017) and Field et al. (2016). We contribute to this literature by reporting on a context where women working as employees in the private sector is discouraged, and where women are more credit constrained than men (World Bank, 2018; Selwaness and Krafft, 2021).

2 Study Setting and Experimental Design

This study took place in Egypt, a rapidly growing lower-middle income country with a population of over 100 million people. High youth unemployment has been a priority issue for policymakers in government and civil society for many years (Assaad et al., 2016; Ghafar, 2016). At the same time, Egypt suffers from extremely low female labor force participation, standing at 23% which comes in as the 10th lowest out of 189 countries that the World Bank collects data for.[4] Of the 10 countries with the lowest rates, 9 are in the Middle East and North Africa region. While the educational attainment of women is similar to that of men, women are much less likely to work and more likely to stop working after they are married (Amer and Atallah, 2019). Survey evidence shows that discrimination against women in

[3] Grants: De Mel et al. (2008) finds increases in profits for men but not women, Fafchamps et al. (2014) finds the same pattern in Ghana, Fiala et al. (2017) finds a positive impact of loans from men but no impact for women from loans or grants, Berge et al. (2015) find no impact on men or women, and Blattman et al. (2019) find no impact for women in the short or long term. Loans: Banerjee et al. (2015a); Angelucci et al. (2015); Attanasio et al. (2015) each find no impacts on profits for women.

[4] India is ranked 11th lowest and has a female labor force participation rate of 23.4%

hiring is widespread, with more than half of enterprises directly admitting it (Osman et al., 2021). Societal expectations for women's personal and professional lives are very different relative to men. This is even more pronounced outside Egypt's two major cities (Cairo and Alexandria), and the areas we work in.

The experiment took place in Qena, which is about 600km south of Cairo and 70km north of Luxor. With a population of 3 million inhabitants, Qena is largely rural and is the ninth poorest state in Egypt (out of 27 states) with a poverty rate of 41% in 2019 (Samir, 2019). The unemployment rate in Qena reached 9.3% in 2017, with a big gap between men and women with female unemployment at 24.8% compared to 6.3% for men.

In collaboration with the Sawiris Foundation and three local microfinance institutions, we designed an experiment that was intended to allow us to estimate the impacts of different types of capital assistance on the development of microenterprises. All three MFI's were experienced in providing micro-loans in these areas, and each worked in separate locations in Qena.[5] This was done as part of the Sawiris Foundation's "Job Creation Competition" which was meant to identify and fund local organizations who had a track record of helping young people find work. While the funding from the foundation allowed the MFI's to provide subsidized loans this did not affect the MFI's screening processes, and individuals were approved for loans using the standard criteria that MFI's had used in the past.

2.1 Randomization and Intervention Details

To recruit the sample, starting in October 2016, the three MFIs advertised that they were providing loans to young people who were interested in starting a business or expanding an existing one. To be eligible to receive financing people needed to be between the ages of 21-35 and needed to go through the normal loan application process including submitting a basic business plan. Individuals were then screened by the NGOs for suitability and conditional on passing that screen their information was sent to the research team for randomization.[6] Recruitment occurred over time with the MFI's going to different locations and recruiting

[5]Our three partner NGOs were (1) Feda, who works in Al Wakf and Nag Hamadi districts, REDEC, who works in Qena and Naqada and Christian Peace, who works in the district of Qos. Outside our experiment, Feda had 361 loan clients, Redec had 8994 and Christian Peace had 179 clients. As of the time we began the study Qena had 123 registered MFIs that served 56,158 active clients with a total outstanding portfolio of 218 million EGP.

[6]All the data and code for the experiment are available at Crépon et al. (2022).

a batch of suitable applicants and then moving on to the next location.[7] Randomization happened by batch (cohort) at the individual level, with one group of the applicants getting a loan, another getting an in-kind grant, a third getting a cash grant and a final group serving as the control.[8]

Loans were provided at slightly below market interest rates, between 15-24% depending on the MFI. A surprise currency devaluation during the early part of this project led to the great majority of loans having a real interest rate below 0. This is important in interpreting our results- while the loans still needed to be paid back with interest, these loans are more generous than the high-interest rates loans that are common in the microcredit industry. The average loan/grant was about 2,400EGP, nearly $750 when using a PPP conversation rate of 3.25. The annual poverty line in Egypt at the time of the study was about 4,500EGP (Sinha, 2020), and so the loan is about 55% of the poverty line. This is similar to the size of the loans studied in Karlan and Zinman (2011) (56% of poverty line) and larger than that studied in Angelucci et al. (2015) (30% of poverty line).

The cash grants were provided by the MFI's to the individuals directly. The recipients were informed that these funds did not need to be paid back. They were lightly encouraged to consider using it to pursue their business objectives as outlined in their loan applications but it was made explicit that they were not required to do so. Similarly, the in-kind grants were provided by the loan officers going to the market with the recipient to buy the items the recipient had outlined in their loan application.[9] The recipient was informed that these goods were a grant and they did not need to repay any portion of them to the MFI.

Since many of the individuals in the sample were starting a business for the first time, all three treatment groups attended an eight hour business training course over two days to cover the basics of running a business. Individuals with business experience were able to

[7]It is possible that people in different villages learned of the nature of the "surprise" grants but we tried to work across areas in a way that would minimize this. We also find high rates of loan take-up which we would not expect if people only applied for the loans because they thought they would get a grant and would renege otherwise.

[8]We did not have an explicit pre-analysis plan, but we did pre-register the trail on the AEA registry before data analysis. The power calculations assumed that we would have 1000 borrowers in control & loans, 600 in cash and in-kind. We assumed we'd find 90% of the sample and that the correlation between baseline and follow up was 0.25. This implied that we would be powered to detect a difference of 0.15 standard deviations between loans and each grant arm, 0.12sd if we combined the grant arms, and 0.11sd if we combined all capital assistance (loans & grants) vs. control.

[9]It is rare for microfinance institutions in this context to cover labor costs. Borrowers are generally aware of this, but in cases where they were not the loan officer clarified the lender policy and the borrower adjusted their ask accordingly.

opt-out of this training.

2.2 Sample Characteristics

Table 1 provides descriptive statistics regarding the make up of our sample as well as tests for balance across treatment groups. The average age in our control group is nearly 29 years old, with 61% being female. Only 10% had a college education, with about a quarter having less than a high school degree.

Given the above mentioned differences in societal gender norms we also produce balance tables split by gender in the appendix (Tables A1 and A2), and we split our analysis of the impacts by gender below. While the average age and educational attainment of men and women are similar they differ in their home and professional lives. Women are much more likely to be married, 67% compared to 39% of men. Women are also much less likely to have any prior work experience, with only 18% having worked before relative to 52% of men. Similarly while 17% of men had an existing business at baseline, only 8% of women do.[10]

To get a sense of the selection on observable characteristics of applications to this program we compare the characteristics of this sample to the average young person in this governorate using the representative sample included in the Egypt Labor Market Panel Survey. Appendix Table A3 shows the differences in characteristics that are collected by the ELMPS and in our own data. We restrict the sample from the ELMPS to individuals between the ages of 21-35 and Column 2 reproduces our summary statistics while also restricting to this age threshold.[11] Compared to the average person in Qena, the women in our sample are slightly more educated, less likely to be married and more likely to have worked in the past. The men in our sample have similar levels of education as the average man in Qena but are also less likely to be married, less likely to be working and less likely to have previously borrowed.

[10]While none of the differences in baseline values are statistically significant some are large. For example, men in the in-kind group are 37 percentage points more like to have worked before. As a robustness check we utilize a double-post-lasso procedure in Appendix B (Belloni et al., 2014), and find that our results are robust to the inclusion of the selected controls.

[11]A small portion of older people managed to join the program, we include these people in all future analysis to ensure the validity of our intent to treat estimates.

2.3 First Stage

Using data from the MFI's we are able to check how well our treatments were implemented relative to the intended randomization. Table 2 shows the proportion of each group that received each form of capital. Since the randomization occurred after people were already approved for a loan we have very high take up rates. About 87% of the loan group ended up taking out the loan, while 99% of the in-kind grant group received the grant, and 98% of the cash group took the grant.[12] No one in the control group managed to get support. The results are nearly identical by gender. Column 5 of Table 2 shows that the amount received conditional on receiving funds is functionally equal across each of the three groups. Appendix Figure D1 provides a histogram with capital amounts by treatment group.

We returned on average 16 months after each cohort received their respective treatments and implemented an in-person follow up survey with the respondents, with an average response rate of 95%. As can be seen in the last line of Table 1, response rates are similar across treatment groups, yet they are lower for those in control. Appendix Table A5 replicates the balancing table 1 on non-attriters and finds that they are balanced on baseline characteristics. Appendix Table B4 includes Lee Bounds for our main outcomes.

3 Average Treatment Effects

Most of our analysis in this section consists of examining intention to treat estimates.[13] Thanks to the randomization we are able to use a simple specification where we regress the outcome variable on indicators for each treatment while including randomization cohort fixed effects (δ).

$$Y_i = \alpha + \beta_L Loan_i + \beta_{IK} In\,Kind_i + \beta_C Cash_i + \delta_{cohort} + u_i \tag{1}$$

Our main tables are split by gender, tables that pool both genders can be found in

[12]Previous work has shown lower than 100% take up of grants (Haushofer and Shapiro, 2016), and in our case we were informed that there was some within-village conflicts between some clients and loan-officers that led to a small number of grants not being made. Appendix Table A4 regresses an indicator for not taking the capital on baseline characteristics and shows that people who do not take out the loan are slightly lower educated.

[13]Since takeup of credit and grants were so high, our treatment on the treated effects would be very similar to our ITT estimates.

Appendix D. To assess the different impacts by gender we run the following fully interacted regression:

$$(2)\quad Y_i = \alpha + \beta_{L_F} Loan_{iF} + \beta_{IK_F} In\,Kind_{iF} + \beta_{C_F} Cash_{iF} + \beta_{L_M} Loan_{iM} + \beta_{IK_M} In\,Kind_{iM} + \beta_{C_M} Cash_{iM} + \gamma_{Female} + \delta_{cohort} + u_i$$

where we interact each treatment arm with a binary for female and include another set of treatment dummies interacted with a binary for male, in addition to adding a gender control. This is functionally equivalent to running separate regressions by gender, with the advantage of being able to compare coefficients to each other directly.[14]

In each table we include the coefficients for each treatment and three additional test statistics. The first is labeled as "Joint" and corresponds to testing the assumption that all three treatment parameters are zero for each gender. The second, labeled as "Same" corresponds to testing the assumption that all three treatment parameters are equal for each gender. The third is the p-value for a test of equality of coefficients across genders.[15] We utilize Huber–White standard errors, and our results are robust to generating standard errors utilizing randomized inference.

As a robustness check we use the *double post lasso procedure* developed in Belloni et al. (2014) which provides a systematic way of selecting control covariates and avoids any risk of specification searching.

$$(3)\qquad Y_i = \alpha + \beta_L Loan_i + \beta_{IK} In\,Kind_i + \beta_C Cash_i + selected(x)_i + \delta_{cohort} + u_i$$

These results are included in Appendix B. We also compute Lee Bounds as an additional robustness check for attrition concerns and report the results in the same appendix.

[14]The one difference between running the specification in equation 2 and running two separate regression by gender is that the cohort-fixed effects could be different in the gender specific regressions. This would likely lead to slight differences in point estimates.

[15]This p-value is equivalent to running a regression of treatment & treatment interacted with female, and then implementing a joint test that the coefficients on the interactions are equal to zero.

3.1 Outside Financing

We begin by reporting impacts on financial market engagement in Table 3. While Table 2 shows that applicants accepted the funds provided to them, it is possible that individuals in the control could have just accessed capital from other lenders, or compensated by using other methods of financing.[16]

We observe substantial differences between treatments and between genders. In column 1 we show that individuals in the loan group are more likely to have taken out additional loans relative to the control group, but column 2 shows that men decrease borrowing from other sources while women do not. This may be because women are more credit constrained than men and have few opportunities to borrow- indeed men in control have more than twice as much borrowing as women in control. Column 3 combines all funding including loans from banks, MFIs, ROSCAs and the experimental loans and grants and shows that women in treatment increase their total funding more than men, largely because men have other opportunities. We also see increases in savings for women who receive the grant, and similar but not statistically significant increases for men.

These estimates imply that in this context women in our sample are more credit constrained than men. While it is complicated to identify the exact mechanisms behind this effect, one interpretation is that the program generated additional opportunities for women and eased their access to funding, maybe because they were able to use the assets they received from the program as collateral on new loans. We find that impacts for women are coming from many women taking out smaller loans, while the results for men are driven by a few individuals who have taken out larger loans.

3.2 Impacts on Business Outcomes

Table 4 outlines the average impacts on business outcomes. All three types of capital assistance lead to large increases in business ownership. To start we note that 27% of men in the control group own their own business (compared to 17% at baseline) while 15% of women

[16]These survey questions asked respondents to only list any loans they received after our intervention and not to include the loan from the existing program. When we matched the responses with the administrative data from the MFIs we found about 28% of those in the loan group were reporting the program loan as the external loan. A match was made when both the program loan and the external loan had a similar amount (+/− 25%) and a similar disbursement date (+/− 2 months) . We turn those matches to 0 in this table, but report the results using the raw data in Appendix Table A15.

do (8% at baseline). These numbers reflect the fact that everyone in our sample had been approved for a loan and so it is not surprising that despite being denied the loan many of them still managed to find a way to start a business. Using the randomization we see that the loan increases business ownership by 14 percentage points for both women and men. The in-kind grant increases it the most, by 24 percentage points for women and 16 for men. The cash grant also leads to large increases, 22 percentage points for women and 12 percentage points for men.

Column 2 reports the impacts on asset accumulation. There are big differences by gender even in control. Men in control have 3326EGP in assets while women in control only have 232EGP worth of assets. Accordingly we see relatively large and precise increases in assets for women, with grants more than tripling the amount of assets for women and loans more than doubling them. For men we see even larger increases but the estimates are much less precise given the increased variance among that group.

Columns 3-5 outline impacts on monthly revenues, expenditures and profits respectively. Individuals who do not have a business are included as “zeros” in these regressions. The survey was implemented after those in the loan group finished repaying their loan so their business measures are comparable to those in the grant groups. Overall we see large increases in all business measures for women, with the biggest increases for those that got the in-kind grant. While for men we see similarly sized increases in monthly business profits, but these effects are not statistically significant due to the increased variance of the outcome.[17]

We also include a standardized index variable in column 6 that standardizes each outcome by gender, adds them together and then standardizes again. This index confirms the increase in business outcomes for women, with the in-kind grant performing best, while showing impacts for men, with loans performing the best. Importantly the impacts of this capital support are greater for women relative to men, with the final row of the table showing that these gender differences are statistically significant.

Despite the large increase in business ownership, only between 29-43% of both men and women in the treatment groups have a business, whereas about 87% took a business loan and over 98% in the grants arms got a grant to help them start a business. We explore this gap

[17] Note that profits are not mechanically calculated as “revenues-expenditures" due to the classical timing problems with that constructed measure and instead we use a direct question about profits last month as our main outcome of interest De Mel et al. (2009).

in Appendix Figure A1. This figure provides insights on the different reasons people report for why they don't have a business. 81% of the control group women claim that they don't have a business because they don't have enough capital. This falls by more than half for those in treatment, with about half of the remaining people saying that they tried to start a business and it failed, while the other half saying that they used the money on non-business activities. Interestingly these excuses do not differ much by treatment group. For men the story is similar, with 68% in control claiming that they didn't have enough capital, this decreases by about a third in treatment, while only about 8% claim to have tried to start a business and failed, with about 19% saying they used the funds on other items. Taking these results at face value would imply that capital constraints still are binding for many in treatment even after our intervention. A large portion of sample tried and failed to start a business, implying that more support may be needed for business success.

3.3 Impacts on Employment, Income and Time-Use

Table 5 reports impacts on employment outcomes. Column 1 considers whether an individual works at all, be it in their own business or working for others. It's worth again noting the stark differences between men and women in the control group. While 24% of women in the control group are working one year after they applied for a loan, 90% of men are working. This showcases an important difference in the ability for individuals who want to work and start their own business to do so without support. Women, as outlined above, have been shown to systematically face a more difficult time in the labor market. The table shows that all three capital treatments lead to economically large and statistically significant increases in economic activity for women, with a 14 percentage point increase from the loan, and 21 percentage point increases from the in-kind and cash grants. Men on the other hand have precisely estimated null effects, with no impact on overall employment from any of the treatments, and tight confidence intervals.

We break the employment impacts apart further in Appendix Table A8 where columns 3 & 5 show that the increase in employment for women is coming nearly all from having their own businesses, while for men the increase in having their own business is coming through a shift away from working for others. Hence while the treatments did not increase labor force participation for men it did change their occupational choices.[18]

We then turn to look at impacts on income. Columns 2 & 3 report the impacts on self-employment and wage earnings respectively, while column 4 combines those to into "total labor earnings". We see large and significant impacts for women, nearly doubling their reported labor earnings. Interestingly the increased income from wage employment for the cash grant and loans help those groups catch up to the larger impact of in-kind grants on profits, leading all three types of capital support to lead to roughly equal increases in total labor earnings. For men we see an increase in self-employment earnings which come primarily at the expense of wage earnings leading to small and statistically insignificant impacts on total labor earnings.

Column 5 reports impacts after combining monthly income from all activities including rents and transfers (but not including the grants provided by the study). All three types of capital support lead to increases in monthly income for women, with a 87EGP increase from the loan, a 171EGP increase from the in-kind grant and a 103EGP increase from the cash grant. All of these coefficients are significant at the 1% level. On average this increase is equivalent to 32% of the poverty line in Egypt at the time of the study. When assessed at the household level this would be closer to an increase equivalent to 9% of the poverty line (since the average household in our sample is 3.5 people).

We see smaller and less precisely estimated impacts on income for men, with the loan leading to an 70EGP increase, the in-kind grant leading to a 45EGP increase and the cash grant leading to a very small decrease, but confidence intervals on these estimates are relatively wide.

Table 6 utilizes data on reported time use to dig deeper on the mechanisms of these income changes. We again see stark differences by gender, with an increase in self-employment hours by women that is coming at the expense of time spent on home activities including child care and household chores. Men on the other hand increase the time spent on self-employment and home agricultural production at the expense of time spent working for others. These shifts are large and precisely estimated, showing that despite negligible effects on income, capital provision led to real occupational shifts for men.

We also consider impacts on non-business outcomes in Appendix Table A6. We find

[18]Osman (2014) provides evidence from a broad sample of students that occupational choices in this context are malleable and can respond to information provision.

evidence of increases in reported quality of life for women in the loan and in-kind groups but not in the cash group. We do not see notable impacts on mental health, decision making power or consumption.

3.4 What can Explain Differential Impacts by Gender?

Earlier work that considered the impact of capital support on enterprise development generally found that returns for men outpaced returns for women, with the modal result showcasing positive impacts for men and no impacts on women (see footnote 3 for a list of related studies). Our findings point in the opposite direction, with much larger impacts for women. We consider some possible explanations.

First, we note that in this context women seem to be more credit constrained than men. Table 3 showed that our treatments are leading to an increase in credit by women (column 2) and an overall increase in funding (column 3). On the other hand men have the opposite response, with negative values indicating that male participant are using the funding from the experiment to substitute away from other credit and financing opportunities they had at their disposal. Men still switch out of working for others into self-employment using their time on wage-activities and instead increase the time they spend on self-employment indicating that credit constraints were not completely absent for them, otherwise we would see no impact of the loan activities. Hence, it is possible that our differential impacts by gender are partially driven by the fact that credit constraints bind more for women than men in this context.

Next, we note the stark difference in the proportion of individuals in the control group who have *any* work by gender. 90% of men in the control have found some kind of income generating activity one year after randomization, while only 24% of women in control have. In line with earlier work in this context, this suggests that the labor market makes it difficult for women to find work while men who want to work seem to be able to find a way to do so (Amer and Atallah, 2019). This implies that the outside option in the labor market is an important consideration for why capital may have differential impacts by gender. In line with this, Table 6 shows that women shift away from uncompensated household work, while men simply shift from working for others to self-employment.

Another reason why we may see stronger impacts for women relative to the earlier literature is because there are fewer cases in our sample of women who are in households with other entrepreneurs. Bernhardt et al. (2019) shows how female enterprise profits may not fully respond to new capital injections because they decide to invest the funds in another business in the household. While we did not collect data on the number of other businesses in the household, we do know that 38% of women in our sample are married and have a spouse who works in the private sector. In the 3 studies examined in Bernhardt et al. (2019), 40-60% of households had multiple enterprises. In Egypt about 10% of men have own a business, but if even half of our 38% had partners with businesses we'd be well below the rates in those other studies.

Other reasons for the departure from the earlier literature are harder to assess. For example, many of the earlier studies are focused on established businesses, whose return to capital may be different from relatively new businesses. In our sample we find no significant difference between recipients who had an existing business at the time of randomization and those who were starting new businesses, and the point estimates suggest women who had a business do better than men who had one at the start. Taken together our results suggest that an essential consideration for understanding the impacts of capital support is both the availability of other types of capital as well as the outside option in the labor market for potential borrowers/recipients. These varying characteristics of the context may help explain the differential gender effects we observe.

4 Heterogeneous Treatment Effects

The impacts reported in Section 3 allow us to assess the differences in the average outcomes for each treatment group. Yet it is possible that those who received a cash grant and those that received an in-kind grant have the same average impact but that this is driven, for instance, by an improvement in outcomes for those at the top of the distribution for cash, while being driven by a more equal increase across the whole group who received the in-kind grant. In this section we turn to testing whether there are heterogeneous treatment effects, primarily by considering how the distributions of income differs across the randomized groups.

We do this using quantile regressions of the following standard form:

$$Q_q(Y) = \alpha_q + \beta_{q,L} Loan_i + \beta_{q,IK} In\,Kind_i + \beta_{q,C} Cash_i + u_i \tag{4}$$

where we estimate the set of quantile effects β_q for each of our treatment arms relative to control. Our main outcome of interest is total monthly labor income since the goal of the program was to increase economic activity and total monthly labor income takes into account all of the choices that individuals make about how to use the funds while providing a good summary measure for how it affects their bottom lines. We bootstrap our standard errors for the quantile regressions utilizing 10,000 replications.

4.1 Quantile and Distributional Tests

Quantile treatment effects allow us to better visualize where in the distribution the impacts are located with appropriate assumptions. We begin by plotting the treatment effects on income for women and men in Figure 2. The figure reveals three important findings. First, Meager (2020) has shown that the impact of micro-loans is located at the top of the distribution,[19] we replicate these results and show that this pattern also holds for cash grants and in-kind grants. The figure includes p-values for equality of distributions relative to control using ranksum tests, showing that the distributional impacts differ for women but not men.

Second, the concentration of impacts at the top of the distribution suggests that the impact of the capital assistance is heterogeneous. To check this claim explicitly we implement a formal test of the equality of all treatment effects across 9 quantile points (the 25, 37.5, 50, 62.5, 75, 87.5, 90, 95 and 97.5 quantiles).[20] We do this by computing the variance matrix of the vector of estimated quantile treatment effects and use Wald tests with 10,000 bootstrap replications to check if the estimated impacts are equal across all points.

This test provides a general way to assess whether the impacts of an intervention are heterogeneous. If we reject the null hypothesis that all of the quantile effects are equal to

[19] Many of the earlier papers on the impacts of microcredit originally report results from quantile regression analysis including Angelucci et al. (2015); Attanasio et al. (2015); Augsburg et al. (2015); Banerjee et al. (2015a); Crépon et al. (2015); Tarozzi et al. (2015).

[20] We begin at the 25th quantile because there is not sufficient variation below it for the estimation to converge. These results are robust to checking along different points in the distribution, we include an example in Appendix Table A9.

each other, this would provide evidence that the impacts of the intervention differs across the distribution.[21] For women we find strong evidence of heterogeneity with a p-value<0.001, while for men we fail to reject with an estimated p-value of 0.186. This method differs from much of the earlier work that attempts to assess the existence of heterogeneous impacts by utilizing subgroup analysis (e.g. interacting treatment with different baseline characteristics) which requires researchers to take a stand on what variables could describe the heterogeneity. Heterogeneity could manifest in non-linear ways which makes sub-group analysis difficult, whereas considering differences across quantiles allows researchers to be agnostic about the dimensions of heterogeneity.

Third, we test if the impacts *across* treatment groups at the same quantile are equal, i.e. is the 95th quantile treatment effect for loans equal to the 95th quantile treatment effect for in-kind grants and for cash grants? Table 7 reports the results. We cannot reject the null, meaning that conditional on the quantile of the effect the impacts of the three different interventions are statistically equivalent for women (p-value=0.791) and men (p-value=0.172). We complement this test with a ranksum test for equal distributions across all three treatments and find that the distributions are statistically equivalent for women (p-value=0.655) and men (p-value=0.894).[22]

Together these results show that while there is strong evidence that there is significant heterogeneity *within* a treatment arm, there is little evidence of differences in impacts at the same quantile *across* treatment arms. Those succeeding with loans are doing about as well as those who are succeeding with cash, and those who are succeeding with in-kind grants. This is striking given the big differences in the nature of the interventions - a loan needs to be repaid, while a grant does not, and ex-ante we would expect the difference between those interventions to be large (in line with earlier research on the returns to grants and the returns to loans). But the difference between the interventions are not as stark as the difference in how the impacts change for those at the top and bottom of the distribution *within* a treatment arm. This shows that in this context "who you are" (i.e. where you are

[21]Because quantile treatment effects are merely measures of how different cumulative distributions are, failing to reject does not imply that there is no heterogeneity, because ranks could change differently across treatments. But rejecting the null would show that there is important heterogeneity in impacts.

[22]Ranksum tests compare the distribution of a variable among two groups. We adapt this test by doing ranksum tests for all three possible pairs and summing the absolute values of the corresponding statistics. We then compute the p-value using randomization inference.

in the distribution) matters more than "what you get" (i.e. which treatment arm you are in).

4.2 Digging further into heterogeneity

In section 4.1 we provide evidence that there is important heterogeneity in the impacts of capital assistance *within* a treatment group, and no evidence of heterogeneity *across* treatment groups. A key question is how to explain this heterogeneity. Of specific interest is whether participants for whom the impact is predicted to be the largest are the same across treatments. In other words, is there a specific "type" of person who succeeds when they get capital support, or do different "types" of people succeed with different types of support?

We test for this in 3 ways. The first way is to ask whether people at the top of the distribution in each assignment group have the same baseline characteristics. We run a type of "balance test", where we compare the baseline characteristics of people in the top 25% of endline outcomes in each group. For example, if college educated individuals did well with cash and high school educated people did well with loans, then we would expect that the baseline education level of people in the top 25% of endline income in the cash group will be higher relative to the education level of those in the top 25% of endline income in the loan group. Any differences in the baseline characteristics of people at the top of the endline income distribution would provide evidence that the different types of capital support help different groups of people.

We test this using a "classification permutation test" as outlined in Gagnon-Bartsch et al. (2019).[23] We implement 2 versions of this test. In the first test we jointly consider the three treatment groups. This examines if the people who reach the top of each of the treatments are observationally equivalent, i.e. does each treatment help the same "type" of person. The second test considers all four assignment groups including the control group. This examines if those that reach the top of the outcome distribution in treatment are different than those that reach the top in control, i.e. does capital assistance lift up people who would not have

[23] In a nutshell, a standard joint test for balance in an experiment runs an OLS regression of a treatment indicator on baseline characteristics and then considers the p-value on the F-test from that regression. Gagnon-Bartsch et al. (2019) provides a method that extends and improves on this in three ways: (1) it shows how to use more flexible regressions (e.g. multinomial logit, etc) for higher predictive power, (2) it shows how to do this jointly for several treatments at the same time, and (3) it describes how to do correct inference using a permutation test.

been as successful without the funds?

Table 8 presents the results. Most characteristics among individuals who end up in the top 25% of the income distribution are both economically and statistically similar across all 4 groups. We fail to reject that average characteristics are equal among the three treatment groups.[24] Furthermore we also fail to reject equality when we consider the top 25% of people in the control group. The only variable where we see a significant difference is "External Pressure to Share Funds" for women, which is much larger in the group assigned to In-Kind grant.[25] This is well in line with previous work in this area (Fafchamps et al., 2014). This is however just one variable among 12 and the joint tests allow us to better account for multiple testing concerns.[26] These results show that there are not large reversals in the people in the top group. Hence, it seems that there is a "type" of applicant who does well with all kinds of capital support, and a "type" that doesn't benefit from any kind of capital support. This provides more evidence that "who you are" is more important than "what you get" in this context.

Second, we use traditional heterogeneity analysis in which we interact theory-led baseline characteristics with treatment status. We considered baseline covariates including whether the recipient already had a business, if they had borrowed before, if they feel pressure to share money with their families, and more. We report the results for women in Appendix Table A13 and for men in Appendix Table A14. While we see some evidence of heterogeneity, for example income for women with children is lower and income is higher if they are pressured to share profits, these results are only marginally significant. This method suffers from two primary drawbacks, (i) dimensions of heterogeneity need to be chosen by the researcher, and important non-linear combinations may exist that would be difficult for the researcher to pre-specify (e.g. highly educated married women without children who come from poorer

[24] We do not interpret this failure to reject as being due to having low power. For example, in Appendix Table A7 we show that there are statistically significant differences between those in the top group and those in the bottom group.

[25] Our "External Pressure to Share Funds" variable is a standardized index of the following 6 baseline variables: (1) There is pressure to share extra profits with other household members, (2) When there is money on hand spouse/family members request some, (3) People who do well in business receive additional requests for money from family, (4) Business equipment is a good way to save money so others don't ask you for money, (5) If they're married, (6) How many people live at home with you?. These 6 questions are meant to provide a measure of how much pressure the applicant may face to share funds.

[26] In appendix tables A10, A11 & A12 we consider the stability in the other quartiles and find that baseline characteristics across treatment groups are also statistically equivalent. This provides more evidence that individual characteristics play a large role in determining endline outcomes.

households- this describes the group that seems to do best as seen in Appendix Table A7), and (ii) standard errors on interaction effects are often much larger than on the main coefficients, leading to under-powered tests. Some of the interaction effects have large coefficients, but also have large standard errors, making it difficult overall to claim that there are any particular characteristics that strongly predict impacts. Overall, the results are suggestive of the existence of important treatment effect heterogeneity, but also that this heterogeneity is difficult to predict, even in cases such as capital support where there is already an extensive prior literature.

The third way is to use the more sophisticated and agnostic machine learning methods developed in Chernozhukov et al. (2020). This method utilizes all of the baseline data to produce a predictive model of endline income for those in control, and another model for those in treatment. By taking the difference between the models it produces a predicted individual treatment effect and groups people by how large of an impact the models predict for them given their baseline characteristics. It utilizes split-sample validation to ensure that the models are not over-fit and that estimates come only from data on other people's outcomes. We describe this method in more detail in Appendix F. Implementing their procedure with our data produces Appendix Figure A2 which shows heterogeneity similar to what we find using quantile regressions but this method is the most power-hungry of the three described in this section, since it uses half of the data to build the models and the other half to test it. Hence we are not able to detect statistically significant heterogeneity. The inability of standard subgroup analysis & generic machine learning methods to produce strong evidence of treatment effect heterogeneity shows the potential utility of using quantile regressions to detect heterogeneity as we do in section 4.1 above.

Taken together we interpret our results as providing strong evidence that *who you are* is more important that *what you get* when considering capital assistance for encouraging higher levels of income. All three types of capital assistance have been shown to have the potential for very different impacts across many different studies, but in this context we are able to hold sampling variation constant and showcase that the impact of individual heterogeneity is larger than the impact of providing a grant or forcing people to repay those funds. This implies that it is just as important for policymakers who want to increase the return from transfers to focus on identifying individuals with high returns as it is to develop new types of ways to help them.

5 Cost Effectiveness

We collected data from the funder and implementing organizations on the costs of the loans and grants. While the costs are relatively straight forward to estimate, the benefits depend on the priorities of the policymaker and assumptions about the longer-term persistence of the estimated impacts. We consider the cost-effectiveness of loans and grants for three potential policy priorities: (i) employment, (ii) income, and (iii) well-being.

The details of our framework and data on actual costs are presented in Appendix C. The amount of the grant disbursed was approximately equal to size of the loan, and so we refer to the capital cost of providing the grant as "C". The loans were subsidized and our data show that the net present value of the capital cost of the loans was approximately 0.1^*C. The implementation costs of the loans and grants were functionally equivalent, since they were dominated by the screening and training costs which were equal across groups. These costs were approximately 0.24^*C. Hence the cost of a grant was 1.24^*C, while the cost of the loan was 0.34^*C, meaning that one grant cost about the same as 3.65 loans.

The stated goal of this program was to "create jobs". Column 1 of Table 5 reports the impacts of the different treatments on employment. For women there is an increase of 0.14 jobs on average in the loan group, and 0.21 additional jobs per person on average across the grant groups. Given our above estimate of the cost differential, these estimates suggest that grants create a job for women for a cost of $1.24C/0.21{=}5.9^*C$ while loans create a job for a cost of $0.34C/0.14{=}2.42^*C$. This implies that loans to women are a more cost-effective way to create employment relative to grants. There is no impact on employment for men implying that both loans and grants are not cost-effective ways to generate male employment in this context.

Next, we consider total income. We assume that the increases in income starts after disbursement and stops after N months. In Appendix Table C2 we estimate the number of months the increase in income would need to be sustained for the intervention to cover its costs. This is short for women and ranges from 17.8 months for in-kind grants to 26.9 months for loans. For men, we estimate small effects on incomes, and so the length of time to recover the cost is many times longer.

Finally, we also consider how effective the treatments are at increasing "well-being". We utilize a simple proxy reported in Column 1 of Table A6 where we ask respondents to rate their lives on a 1-10 scale. We find that women in the loan and in-kind treatments report significant increases, while women in the cash grant group do not. We find positive but insignificant impacts for men. Using our cost estimates this implies that loans can increase "well-being" for women by 1 "util" for a cost of $1.03^{*}C$, while in-kind grants would cost $2.76^{*}C$ for the same increase.

Together these analyses show that the most cost-effective type of capital assistance will depend both on the outcome that the policymaker is seeking to increase (e.g. jobs vs. income vs. well-being) and how those outcomes change over time. For women, subsidized loans are the most cost-effective way to increase employment and well-being, while in-kind grants are the most cost effective way to increase income.

6 Discussion and Conclusion

We implemented a large randomized experiment where we provided young existing and would-be entrepreneurs with either a subsidized loan, an in-kind grant, or a cash grant and compared them to a control group that received no assistance. One year later, we found large positive impacts of capital assistance on business performance, with larger impacts for women relative to men. We found a shift towards self-employment for both genders, coming at the extensive margin for women (i.e. more women working) leading to a increase in total income. For men, the increase in self-employment came at the intensive margin (i.e. men shifting from working for others to self-employment), leading to no significant impact on total income.

While we highlight how people at the top of the distribution benefit from all types of capital, it's also striking that such a large group of people at the bottom of the distribution don't benefit from any type of capital support. Hence, while improved targeting can lead to much better average impacts of these programs, it remains essential to identify different ways to support those at the bottom of the distribution.

It is worth noting several limitations to our analysis. First, while we have data a little over a year after disbursement, we lack longer term data, placing our estimates in the "medium-term" category relative to other papers that have longer term data, stretching as far as 9-years after disbursement (Blattman et al., 2020). While our sample is large and benefits from high take-up relative to other studies in this literature (Banerjee et al., 2015b), we lack power to consider impacts for important subgroups, like men who had an existing business, which is a subgroup that dominates much of the other work in this area. Due to the surprise currency devaluation our subsidized loan had an effective interest rate of zero, making our loans different from many of the high interest rates loans studied in the past. Of course, as with any study implemented in a certain time and place, we are limited in how our estimates would extend to other contexts.

Overall, we believe these results lend themselves to several avenues for future research. When considering the impacts of capital assistance, testing different methods to ex-ante identify individuals with the highest returns to capital remains an important yet challenging task (e.g. McKenzie and Sansone (2019); Hussam et al. (2020); Bryan et al. (2021)). Implementing a similar set of tests of the impacts of different types of capital provision on large and more mature businesses would help tackle one important dimension of generalizability. Returning to these businesses in the longer term will allow us to see how these results evolve over time. Finally, a deeper delve into the impacts of the "repayment burden" on business outcomes could shed light on the relationship between real interest rates and the benefits of microfinance (Karlan and Zinman, 2009).

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Table 1: Baseline Balance

	Treatment Status			
	Control	Microcredit	In-Kind Grant	Cash Grant
	(1)	(2)	(3)	(4)
Age	28.88	-0.38	-0.39	-0.37
	{5.50}	(0.23)	(0.26)	(0.26)
Male	0.40	0.02	0.02	-0.01
	{0.49}	(0.02)	(0.03)	(0.02)
College Education	0.10	0.00	0.02	-0.02
	{0.30}	(0.01)	(0.02)	(0.01)
High School Education	0.59	0.02	-0.03	0.01
	{0.49}	(0.02)	(0.03)	(0.02)
Less than High School	0.28	-0.01	0.01	0.02
	{0.45}	(0.02)	(0.02)	(0.02)
Worked Before	0.31	0.01	0.01	-0.03
	{0.46}	(0.02)	(0.02)	(0.02)
Has a Business	0.12	0.01	-0.02	-0.01
	{0.32}	(0.01)	(0.02)	(0.02)
Single	0.40	-0.02	0.02	-0.02
	{0.49}	(0.02)	(0.02)	(0.02)
Married	0.55	0.04	-0.01	0.03
	{0.50}	(0.02)	(0.03)	(0.02)
Has Kids	0.50	0.04	0.00	0.01
	{0.50}	(0.02)	(0.03)	(0.03)
Low Family Income	0.31	-0.02	-0.03	-0.04
	{0.46}	(0.02)	(0.02)	(0.02)
Has Previous Borrowing	0.11	-0.02	-0.01	-0.01
	{0.31}	(0.01)	(0.02)	(0.01)
External Pressure to Share Funds	-0.08	0.06	0.07	0.07
	{1.10}	(0.04)	(0.05)	(0.05)
Received Training		0.83	0.02	-0.01
		{0.00}	(0.01)	(0.01)
Global test P-Value	0.11			
N	1020	994	604	618
Response Rate	0.88	0.07***	0.08***	0.08***

Notes: Control group means are listed in column 1, with standard deviations in brackets. Differences between the control group and each individual group are found in subsequent columns. The final row includes the mean and standard deviation of the microcredit group in column 2 and reports the difference between that group and the other treatment groups in columns 3 and 4 (since no one in control got training). The joint p-value comes from a multinomial logistic regression that tries to predict treatment assignment using the baseline characteristics. The number of observations reflect the size of the sample in that particular treatment arm. Heteroskedasticity-robust standard errors in parentheses. Regressions include cohort fixed effects. Significance * .10; ** .05; *** .01.

Table 2: Compliance with the experimental protocol by gender

	Amount Received	Received			Conditional Amount
		Microcredit	In-Kind Grant	Cash Grant	
	(1)	(2)	(3)	(4)	(5)
Panel A: Female Participants					
Micro credit	2030	0.882	0.000	0.000	2300
In kind grant	2368	0.000	0.992	0.000	2389
Cash grant	2337	0.000	0.000	0.972	2406
Control	0.000	0.000	0.000	0.000	0.000
Observations	1944	1944	1944	1944	1252
Panel B: Male Participants					
Micro credit	2044	0.862	0.000	0.000	2373
In kind grant	2410	0.000	0.985	0.000	2449
Cash grant	2365	0.000	0.000	0.979	2417
Control	0.000	0.000	0.000	0.000	0.000
Observations	1349	1349	1349	1349	864

Notes: The table uses administrative data received from implementing NGOs based on actual amounts disbursed to each individual in the study. Column 5 reports the amount of capital received conditional on receiving the loan/grant.

Table 3: Utilization of Financial Instruments

	Any External Loan (1)	Total External Loans (2)	Total Funding (3)	Total Savings (4)
Panel A: Female Participants				
Micro credit	0.216***	93	2245***	67
	(0.029)	(156)	(207)	(49)
In kind grant	0.021	331	3253***	247***
	(0.033)	(214)	(338)	(86)
Cash grant	0.026	101	2669***	151**
	(0.032)	(190)	(272)	(64)
Mean	0.378	1370	1839	153
Joint significance of treatments	0.000	0.494	0.000	0.010
Same effect across treatments	0.000	0.537	0.012	0.102
N	1835	1835	1835	1834
Panel B: Male Participants				
Micro credit	0.164***	-928***	1160**	146
	(0.036)	(352)	(500)	(249)
In kind grant	0.037	-60	2386***	157
	(0.042)	(442)	(570)	(283)
Cash grant	-0.019	-771*	1574***	344
	(0.042)	(400)	(601)	(387)
Mean	0.440	3038	4238	935
Joint significance of treatments	0.000	0.018	0.000	0.819
Same effect across treatments	0.000	0.075	0.061	0.868
N	1240	1240	1240	1230
p-value: $\beta_{female} = \beta_{male}$	0.419	0.037	0.177	0.869

Notes: Column 1 is a binary variable that is equal to 1 if the individual took any loan from a bank, an MFI, family member or through ROSCA (other than the experiment loan). Column 2 is the total of loans taken from a bank, an MFI, family member or through ROSCA in addition to the experiment loan. Amounts are winsorized at the 99th percentile. The "Joint" row reports the p-value for the test for joint significance of the three treatment coefficients. The "Same" row reports the p-value for testing the hypotheses that there is no difference in the treatment coefficients. The final row reports the p-value from a test of equality of treatment coefficients by gender. Heteroskedasticity-robust standard errors in parentheses. Regressions include cohort fixed effects. Significance * .10; ** .05; *** .01.

Table 4: Impacts on Business Outcomes

	Has Business (1)	New Asset (2)	Monthly Revenue (3)	Monthly Expenditure (4)	Monthly Profit (5)	Business Index (6)
Panel A: Female Participants						
Micro credit	0.14***	363***	205***	153**	63***	0.35***
	(0.02)	(106)	(77)	(64)	(19)	(0.08)
In kind grant	0.24***	515***	491***	374***	133***	0.66***
	(0.03)	(142)	(114)	(89)	(29)	(0.11)
Cash grant	0.22***	471***	273***	203***	60***	0.45***
	(0.03)	(143)	(79)	(67)	(16)	(0.09)
Mean	0.15	232	248	204	59	0.00
Joint significance of treatments	0.00	0.00	0.00	0.00	0.00	0.00
Same effect across treatments	0.00	0.61	0.06	0.06	0.04	0.04
N	1835	1835	1834	1833	1834	1835
Panel B: Male Participants						
Micro credit	0.14***	1833*	1102	708	136	0.20**
	(0.03)	(1084)	(709)	(634)	(103)	(0.09)
In kind grant	0.16***	-494	-118	-136	95	0.09
	(0.04)	(915)	(524)	(476)	(111)	(0.08)
Cash grant	0.12***	1561	163	-293	64	0.10
	(0.04)	(1366)	(550)	(477)	(102)	(0.08)
Mean	0.27	3326	2234	1862	511	0.00
Joint significance of treatments	0.00	0.08	0.37	0.42	0.59	0.13
Same effect across treatments	0.73	0.04	0.23	0.25	0.80	0.42
N	1240	1240	1237	1230	1236	1240
p-value: $\beta_{female} = \beta_{male}$	0.070	0.083	0.131	0.166	0.634	0.000

Notes: Column 2 are assets bought during the year after randomization. Assets include business premises, land, furniture, equipment, and vehicles. Columns 3-5 are reported at the monthly level. Amounts are winsorized at the 99th percentile. The "Joint" row reports the p-value for the test for joint significance of the three treatment coefficients. The "Same" row reports the p-value for testing the hypotheses that there is no difference in the treatment coefficients. The final row reports the p-value from a test of equality of treatment coefficients by gender. Heteroskedasticity-robust standard errors in parentheses. Regressions include cohort fixed effects. Significance * .10; ** .05; *** .01.

Table 5: Impacts on Employment and Monthly Income

	Has Work (1)	Self Employment (2)	Wage Employment (3)	Labor Income (4)	Total Income (5)
Panel A: Female Participants					
Micro credit	0.14***	63***	31*	94***	87**
	(0.03)	(19)	(18)	(26)	(36)
In kind grant	0.21***	133***	-15	118***	171***
	(0.03)	(29)	(16)	(33)	(46)
Cash grant	0.21***	60***	59**	119***	104***
	(0.03)	(16)	(25)	(29)	(38)
Mean	0.24	59	68	127	303
Joint significance of treatments	0.000	0.000	0.006	0.000	0.001
Same effect across treatments	0.044	0.037	0.003	0.689	0.222
N	1835	1834	1835	1834	1834
Panel B: Male Participants					
Micro credit	-0.01	136	-103	53	70
	(0.02)	(103)	(76)	(107)	(106)
In kind grant	0.02	95	-47	47	45
	(0.03)	(111)	(90)	(121)	(120)
Cash grant	0.00	64	-85	-21	-13
	(0.03)	(102)	(90)	(114)	(113)
Mean	0.90	511	1140	1652	1661
Joint significance of treatments	0.787	0.593	0.568	0.911	0.880
Same effect across treatments	0.595	0.799	0.824	0.808	0.785
N	1240	1236	1239	1235	1235
p-value: $\beta_{female} = \beta_{male}$	0.000	0.634	0.194	0.732	0.655

Notes: Column 2 reports income from self-employment and is the same as the "profits" column in Table 4. Column 4 is the total of columns 2 and 3. Column 5 is the total of columns 2, 3 and family and government transfers, but does not include the transfers from the experiment. Amounts are winsorized at the 99th percentile. The "Joint" row reports the p-value for the test for joint significance of the three treatment coefficients. The "Same" row reports the p-value for testing the hypotheses that there is no difference in the treatment coefficients. The final row reports the p-value from a test of equality of treatment coefficients by gender. Heteroskedasticity-robust standard errors in parentheses. Regressions include cohort fixed effects. Significance * .10; ** .05; *** .01.

Table 6: Time Use

	Hours Spent on: Employment	Self-Employment	Home Agri.	Household Chores	Econ Time -Use Index
	(1)	(2)	(3)	(4)	(5)
Panel A: Female Participants					
Micro credit	0.94	5.01***	0.17	-5.54*	0.24***
	(0.71)	(1.17)	(0.44)	(2.84)	(0.06)
In kind grant	0.11	8.61***	0.33	-7.59**	0.34***
	(0.84)	(1.42)	(0.56)	(3.30)	(0.08)
Cash grant	1.48*	7.80***	0.09	-5.86*	0.37***
	(0.84)	(1.35)	(0.50)	(3.08)	(0.07)
Mean	3.38	5.62	2.97	56.43	0.00
Joint significance of treatments	0.237	0.000	0.948	0.070	0.000
Same effect across treatments	0.363	0.039	0.919	0.817	0.204
N	1835	1835	1366	1366	1835
Panel B: Male Participants					
Micro credit	-5.27***	6.09***	0.90**	0.06	0.16*
	(1.97)	(2.03)	(0.43)	(0.94)	(0.09)
In kind grant	-4.18*	5.75***	1.17*	2.44*	0.22*
	(2.25)	(2.18)	(0.63)	(1.38)	(0.12)
Cash grant	-5.40**	5.73**	1.13*	0.09	0.18
	(2.26)	(2.30)	(0.61)	(1.09)	(0.12)
Mean	33.77	13.96	1.15	5.45	0.00
Joint significance of treatments	0.027	0.007	0.047	0.272	0.101
Same effect across treatments	0.861	0.984	0.890	0.153	0.876
N	1240	1240	892	894	1240
p-value: $\beta_{female} = \beta_{male}$	0.007	0.326	0.431	0.032	0.544

Notes: This table reports weekly hours spent on each activity. Column 4 includes hours spent in the household on cleaning, maintenance, gathering water or fuel and on childcare. Column 6 is an index of columns 1,2,3. Hours are winsorized at the 99th percentile. The "Joint" row reports the p-value for the test for joint significance of the three treatment coefficients. The "Same" row reports the p-value for testing the hypotheses that there is no difference in the treatment coefficients. The final row reports the p-value from a test of equality of treatment coefficients by gender. Heteroskedasticity-robust standard errors in parentheses. Regressions include cohort fixed effects. Significance * .10; ** .05; *** .01.

Table 7: Testing Heterogeneity Within & Across Treatment Arms

	p-value
Panel A: Female Participants	
Quantile effects in each treatment arm are equal	<0.001
Quantile effects across treatment arms are equal	0.791
Ranksum test of equal distributions across arms	0.766
Panel B: Male Participants	
Quantile effects in each treatment arm are equal	0.175
Quantile effects across treatment arms are equal	0.172
Ranksum test of equal distributions across arms	0.554

Notes:This table reports p-values for three different types of test. The first is to test for heterogeniety within treatment arms. This is implemented by computing values $q \in \{.25, .375, .50, .625, .75, .875, .90, .95, .975\}$, and testing if $\beta_{.25,T} = ... = \beta_{.975,T}$ using wald tests with 10,000 bootstrap replications. Next it tests if treatment effects across arms are equal by testing if $\beta_{q,L} = \beta_{q,IK} = \beta_{q,C}$ in a similar fashion. Finally it tests if distributions are equivalent across arms by computing the sum of the absolute value of the three 2x2 ranksum statistics and computing its p-value using randomization inference with 10,000 permutations.

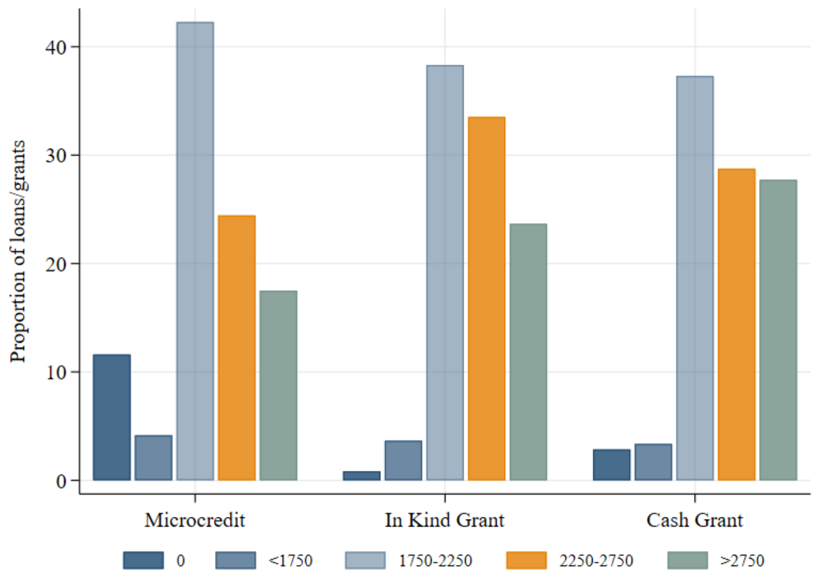
Table 8: Balancing among top 25 participants in each assignment group

	Mean in assignment groups				p-values	
	Control	Microcredit	In-Kind	Cash	3 treatment groups	4 assignment groups
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Female Participants						
Age	31.04	29.69	28.99	28.86	0.99	0.97
College Education	0.12	0.12	0.15	0.07	0.07	0.14
High School Education	0.47	0.57	0.49	0.49	0.93	0.40
Less than High School Education	0.38	0.30	0.34	0.38	0.61	0.56
Worked Before	0.16	0.14	0.21	0.15	0.69	0.77
Single	0.11	0.25	0.22	0.22	0.73	0.94
Married	0.79	0.69	0.75	0.68	0.15	0.41
Low Family Income	0.43	0.39	0.28	0.31	0.91	0.34
Has a business	0.05	0.07	0.08	0.07	0.39	0.58
Any Borrowing	0.14	0.17	0.15	0.09	0.15	0.26
External Pressure to Share Funds	0.11	-0.03	0.27	-0.03	0.01	0.07
Has Kids	0.80	0.65	0.74	0.68	0.26	0.38
Balancing test p-values					0.748	0.806
Panel B: Male Participants						
Age	28.37	27.78	27.88	28.88	0.15	0.12
College Education	0.13	0.15	0.14	0.10	0.89	0.83
High School Education	0.66	0.64	0.61	0.68	0.18	0.49
Less than High School Education	0.16	0.16	0.19	0.22	0.73	0.88
Worked Before	0.45	0.42	0.53	0.34	0.15	0.35
Single	0.57	0.56	0.63	0.46	0.06	0.21
Married	0.42	0.43	0.36	0.53	0.09	0.23
Low Family Income	0.28	0.28	0.27	0.31	0.34	0.24
Has a business	0.13	0.13	0.14	0.14	0.58	0.77
Any Borrowing	0.12	0.11	0.17	0.12	0.34	0.66
External Pressure to Share Funds	-0.04	-0.03	0.07	-0.07	0.84	0.88
Has Kids	0.36	0.41	0.31	0.42	0.10	0.31
Balancing test p-values					0.876	0.327

The table presents the average of each characteristics for individuals in the top 25% of total income at endline in each assignment group. Column 5 presents the p-value of the test of equality of means among all three treatment groups. Column 6 presents the p-value of the test of equality of means among all four assignment groups. The group p-values are listed at the bottom of each panel and are presents the results of the joint balancing test by computing the test statistic outlined in Gagnon-Bartsch et al. (2019).

Figure 1: Capital Assistance Received

Female



Male

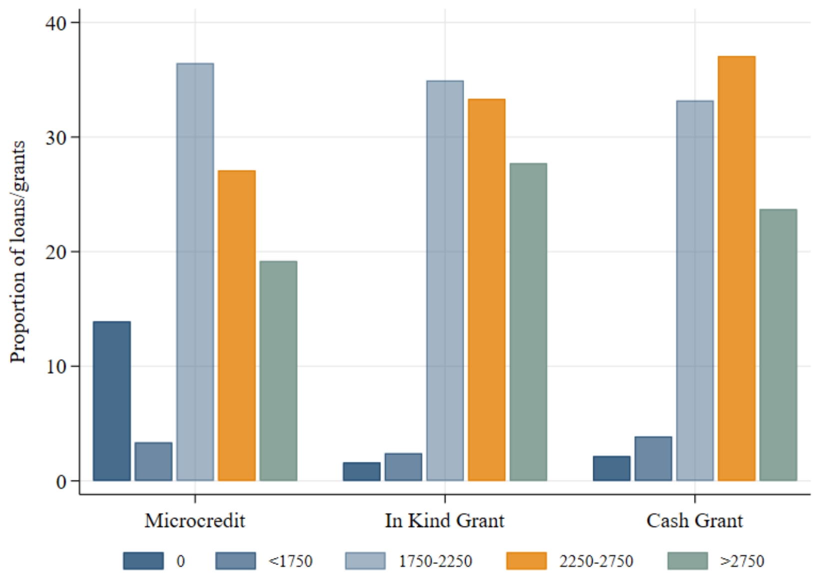
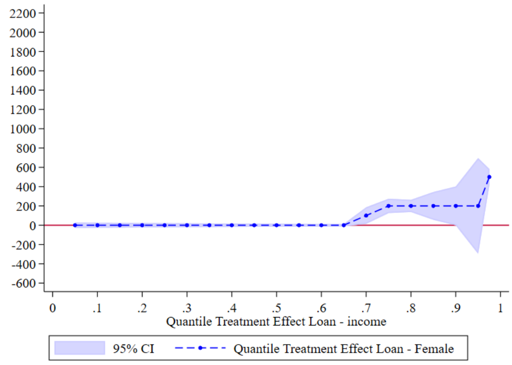
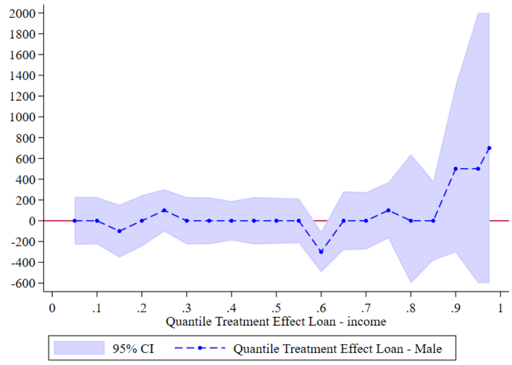
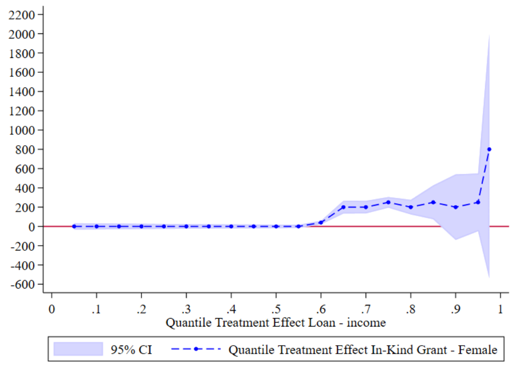
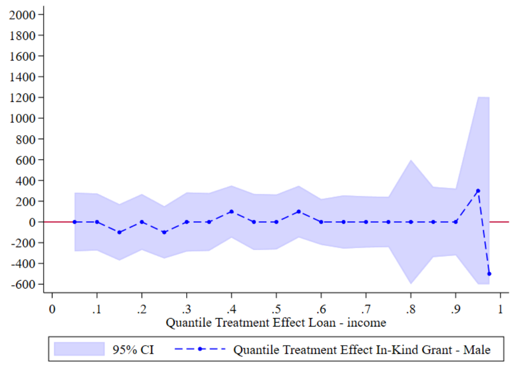
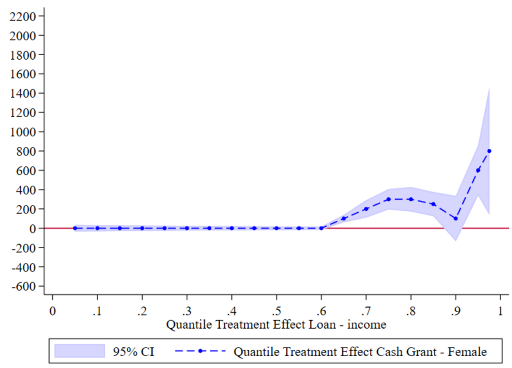
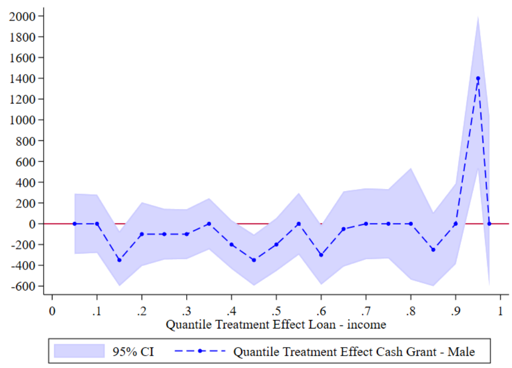


Figure 2: Quantile Treatment Effects for Total Income

	Female	Male
Microcredit		
		
	Ranksum: 0.007	Ranksum: 0.969
In Kind Grant		
		
	Ranksum: <0.001	Ranksum: 0.964
Cash Grant		
		
	Ranksum: 0.001	Ranksum: 0.689

Notes: Estimates by gender of equation (4). Each figure plots the corresponding estimated coefficients. Ranksum p-values are obtained by randomization inference using 10,000 permutations

Online Appendix

Is It Who You Are or What You Get? Comparing the Impacts of Loans and Grants on Microenterprise Development

Bruno Crépon, Mohamed El Komi and Adam Osman

Appendix 1: Additional Tables and Figures

Table A1: Baseline Balance (Women)

	Treatment Status			
	Control	Microcredit	In-Kind Grant	Cash Grant
	(1)	(2)	(3)	(4)
Age	29.73	-0.27	-0.19	-0.08
	{6.99}	(0.440)	(0.480)	(0.475)
College Education	0.09	-0.01	0.02	-0.02
	{0.29}	(0.016)	(0.020)	(0.017)
High School Education	0.55	0.04	-0.02	0.00
	{0.5}	(0.028)	(0.032)	(0.031)
Less than High School	0.32	-0.02	0.01	0.02
	{0.47}	(0.025)	(0.029)	(0.029)
Worked Before	0.18	0.03	-0.01	0.02
	{0.38}	(0.020)	(0.023)	(0.022)
Has a Business	0.08	0.02	0.00	0.00
	{0.28}	(0.015)	(0.018)	(0.017)
Single	0.26	-0.05	0.01	-0.02
	{0.44}	(0.024)	(0.029)	(0.027)
Married	0.67	0.08	0.00	0.02
	{0.47}	(0.026)	(0.031)	(0.029)
Has Kids	0.63	0.06	0.02	0.02
	{0.48}	(0.027)	(0.031)	(0.030)
Low Family Income	0.33	-0.01	-0.03	-0.04
	{0.47}	(0.021)	(0.025)	(0.025)
Has Previous Borrowing	0.12	-0.03	0.00	-0.02
	{0.32}	(0.017)	(0.021)	(0.019)
External Pressure to Share Funds	-0.07	0.08	0.09	0.05
	{1.09}	(0.055)	(0.067)	(0.064)
Received Training		0.84	0.87	0.84
		(0.012)	(0.013)	(0.013)
Global test P-Value	0.301			
N	622	578	358	386

Notes: Control group means are listed in column 1, with standard deviations in brackets. Differences between the control group and each individual group are found in subsequent columns. The final row includes the mean and standard deviation of the microcredit group in column 2 and reports the difference between that group and the other treatment groups in columns 3 and 4 (since no one in control got training). The joint p-value comes from a multinomial logistic regression that tries to predict treatment assignment using the baseline characteristics. The number of observations reflect the size of the sample in that particular treatment arm. Heteroskedasticity-robust standard errors in parentheses. Regressions include cohort fixed effects. Significance * .10; ** .05; *** .01.

Table A2: Baseline Balance (Men)

	Treatment Status			
	Control	Microcredit	In-Kind Grant	Cash Grant
	(1)	(2)	(3)	(4)
Age	28.21	-0.73	-0.54	-0.52
	{4.37}	(0.373)	(0.410)	(0.433)
College Education	0.11	0.03	0.03	-0.02
	{0.32}	(0.023)	(0.027)	(0.025)
High School Education	0.65	0.00	-0.04	0.05
	{0.48}	(0.033)	(0.039)	(0.039)
Less than High School	0.21	-0.03	0.00	-0.02
	{0.41}	(0.028)	(0.032)	(0.033)
Worked Before	0.49	-0.03	0.00	-0.07
	{0.5}	(0.027)	(0.030)	(0.033)
Has a Business	0.16	-0.02	-0.05	-0.03
	{0.37}	(0.023)	(0.025)	(0.026)
Single	0.6	0.01	0.02	0.00
	{0.49}	(0.034)	(0.038)	(0.039)
Married	0.38	0.01	-0.02	0.02
	{0.48}	(0.034)	(0.037)	(0.038)
Has Kids	0.31	0.01	-0.01	-0.04
	{0.46}	(0.032)	(0.036)	(0.037)
Low Family Income	0.27	-0.02	-0.02	-0.03
	{0.44}	(0.023)	(0.026)	(0.028)
Has Previous Borrowing	0.1	0.00	-0.01	0.00
	{0.30}	(0.019)	(0.023)	(0.023)
External Pressure to Share Funds	-0.09	0.02	0.05	0.09
	{1.12}	(0.068)	(0.078)	(0.076)
Received Training		0.80	0.84	0.80
		(0.018)	(0.018)	(0.018)
Global test P-Value	0.134			
N	426	426	259	238

Notes: Control group means are listed in column 1, with standard deviations in brackets. Differences between the control group and each individual group are found in subsequent columns. The final row includes the mean and standard deviation of the microcredit group in column 2 and reports the difference between that group and the other treatment groups in columns 3 and 4 (since no one in control got training). The joint p-value comes from a multinomial logistic regression that tries to predict treatment assignment using the baseline characteristics. The number of observations reflect the size of the sample in that particular treatment arm. Heteroskedasticity-robust standard errors in parentheses. Regressions include cohort fixed effects. Significance * .10; ** .05; *** .01.

Table A3: Comparison to ELMPS Sample

	ELMPS 2018 (1)	Baseline (2)	Difference (3)
Panel A: Female Participants			
Age	27.56	27.98	0.42***
	(4.42)	(4.20)	(0.20)
Less than High School	0.42	0.30	-0.12***
	(0.42)	(0.49)	(0.022)
High School Education	0.41	0.57	0.16***
	(0.41)	(0.49)	(0.023)
Some College Education	0.03	0.03	0.00
	(0.17)	(0.18)	(0.00)
College Education	0.14	0.10	-0.04***
	(0.34)	(0.30)	(0.01)
Married	0.78	0.70	-0.09***
	(0.41)	(0.46)	(0.019)
Has Kids	0.66	0.64	-0.02
	(0.47)	(0.48)	(0.022)
Works at All	0.04	0.16	0.10***
	(0.22)	(0.36)	(0.012)
Has a Business	0.01	0.10	0.08***
	(0.11)	(0.30)	(0.01)
Has Previously Borrowed	0.10	0.09	-0.01
	(0.31)	(0.29)	(0.01)
N	632	1740	
Panel B: Male Participants			
Age	27.50	27.63	0.13
	(4.60)	(3.98)	(0.22)
Less than High School	0.19	0.21	0.01
	(0.40)	(0.40)	(0.02)
High School Education	0.61	0.64	0.02
	(0.49)	(0.48)	(0.02)
Some College Education	0.02	0.03	0.00
	(0.16)	(0.17)	(0.01)
College Education	0.14	0.12	-0.02
	(0.36)	(0.33)	(0.02)
Married	0.47	0.38	-0.09***
	(0.50)	(0.49)	(0.02)
Works at All	0.77	0.47	-0.31***
	(0.42)	(0.50)	(0.02)
Has a Business	0.09	0.15	0.05***
	(0.30)	(0.36)	(0.02)
Has Previously Borrowed	0.19	0.10	-0.08***
	(0.39)	(0.30)	(0.02)
N	578	1275	

Notes: Column 1 represents the average young person in Qena using the Egypt Labor Market Panel Survey. We restrict the sample from the ELMPS to individuals between the ages of 21-35 and Column 2 reproduces our summary statistics while also restricting to this age threshold. Column 3 reports the difference between the two samples. Heteroskedasticity-robust standard errors in parentheses. Significance * .10; ** .05; *** .01.

Table A4: Determinants of Not Taking Up the Treatment

	All	Microcredit	In-Kind Grant	Cash Grant
	(1)	(2)	(3)	(4)
Age	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Female	-0.01	-0.02	0.02	-0.00
	(0.02)	(0.03)	(0.04)	(0.03)
College Education	0.03	0.08	0.01	-0.02
	(0.07)	(0.09)	(0.10)	(0.10)
High School Education	0.04	0.08	-0.01	0.04
	(0.06)	(0.09)	(0.09)	(0.09)
Less than High School Education	0.05	0.04	0.04	0.08
	(0.07)	(0.09)	(0.09)	(0.09)
Worked Before	-0.06	-0.09*	0.03	-0.12**
	(0.03)	(0.04)	(0.04)	(0.04)
Single	0.01	0.03	0.07	-0.12
	(0.06)	(0.09)	(0.09)	(0.09)
Married	0.01	0.06	0.00	-0.04
	(0.05)	(0.07)	(0.08)	(0.07)
Low Family Income	-0.03	0.00	-0.03	-0.09**
	(0.02)	(0.03)	(0.03)	(0.03)
Has a Business	0.05	0.06	-0.06	0.15*
	(0.04)	(0.06)	(0.07)	(0.06)
Has Previous Borrowing	-0.03	-0.04	-0.02	-0.05
	(0.03)	(0.04)	(0.04)	(0.04)
External Pressure to Share Funds	-0.01	-0.03*	0.01	0.01
	(0.01)	(0.02)	(0.02)	(0.02)
Has Kids	0.03	0.06	0.06	-0.04
	(0.04)	(0.05)	(0.05)	(0.05)
Constant	0.73***	0.45**	0.37*	0.56***
	(0.11)	(0.15)	(0.16)	(0.16)
Observations	2118	1310	1066	1072

Notes: This table reports the results of 4 separate regressions of a binary on if they took up the treatment on the characteristics listed in the rows of the tables. The number of observations reflect the size of the sample in that particular treatment arm. Heteroskedasticity-robust standard errors in parentheses. Regressions include cohort fixed effects. Significance * .10; ** .05; *** .01.

Table A5: Baseline Balance (Non-attriters)

	Treatment Status			
	Control	Microcredit	In-Kind Grant	Cash Grant
	(1)	(2)	(3)	(4)
Age	28.9	-0.331	-0.320	-0.328
	{5.4}	(0.240)	(0.263)	(0.265)
Gender (Male)	0.4	0.023	0.023	0.000
	{0.5}	(0.022)	(0.026)	(0.025)
College Education	0.1	-0.002	0.024	-0.020
	{0.3}	(0.014)	(0.017)	(0.014)
High School Education	0.6	0.020	-0.024	0.009
	{0.5}	(0.022)	(0.025)	(0.025)
Less than High School Education	0.3	-0.013	0.003	0.014
	{0.5}	(0.020)	(0.023)	(0.023)
Worked Before	0.3	0.005	0.011	-0.034
	{0.5}	(0.019)	(0.022)	(0.021)
Has a business	0.1	0.008	-0.014	-0.004
	{0.3}	(0.014)	(0.016)	(0.016)
Single	0.4	-0.015	0.029	-0.009
	{0.5}	(0.022)	(0.025)	(0.025)
Married	0.6	0.028	-0.018	0.011
	{0.5}	(0.023)	(0.026)	(0.025)
Has Kids	0.5	0.017	-0.016	-0.014
	{0.5}	(0.023)	(0.026)	(0.026)
Low Family Income	0.3	-0.019	-0.026	-0.041
	{0.5}	(0.017)	(0.019)	(0.019)
Any Borrowing	0.1	-0.021	-0.004	-0.018
	{0.3}	(0.014)	(0.016)	(0.015)
External Pressure to Share Funds	0.0	0.014	0.071	0.044
	{1.0}	(0.042)	(0.049)	(0.048)
Received Training		0.8	0.020	-0.004
		{0.4}	(0.011)	(0.010)
Global test P-Value	0.820			
N	902	942	582	598

Notes: Control group means are listed in column 1, with standard deviations in brackets. Differences between the control group and each individual group are found in subsequent columns. The joint p-value comes from a multinomial logistic regression that tries to predict treatment assignment using the baseline characteristics. The number of observations reflect the size of the sample in that particular treatment arm. Heteroskedasticity-robust standard errors in parentheses. Regressions include cohort fixed effects. Significance * .10; ** .05; *** .01.

Table A6: Impacts on Non-Business Outcomes

	Quality of Life (1)	Mental Health (2)	Physical Health (3)	Decision Power (4)	Consump- -tion (5)
Panel A: Female Participants					
Micro credit	0.33**	-0.03	0.06	0.04	-29
	(0.14)	(0.06)	(0.06)	(0.05)	(153)
In kind grant	0.45***	-0.04	0.19***	0.09	62
	(0.16)	(0.07)	(0.07)	(0.06)	(168)
Cash grant	0.01	0.05	0.18***	0.07	-102
	(0.15)	(0.07)	(0.07)	(0.06)	(174)
Control Mean	3.38	0.00	3.06	2.08	3348
Joint significance of treatments	0.007	0.595	0.015	0.504	0.835
Same effect across treatments	0.030	0.396	0.116	0.678	0.661
N	1835	1835	1835	1835	1415
Panel B: Male Participants					
Micro credit	0.13	0.10	-0.02	0.03	320
	(0.16)	(0.07)	(0.07)	(0.06)	(287)
In kind grant	0.14	0.09	0.15*	-0.13**	917**
	(0.18)	(0.08)	(0.09)	(0.07)	(400)
Cash grant	0.22	0.11	-0.03	0.08	83
	(0.18)	(0.08)	(0.09)	(0.07)	(319)
Control Mean	3.40	0.00	2.78	2.35	4233
Joint significance of treatments	0.648	0.426	0.217	0.027	0.137
Same effect across treatments	0.894	0.980	0.115	0.009	0.182
N	1240	1240	1240	1240	954

Notes: Column 1 is measured by asking participants to report on a scale, or "ladder steps", from 1 to 10 which step they think they stand in terms of happiness with their current achievements in life, ten being the best. Column 2 is an index of questions on how often participants felt worried, tense, anxious or depressed. Column 3 is a self-reported score on physical health from 1 to 5 with 1 being poor health and 5 excellent health. Column 4 is an index using three separate questions about participants' ability to take decision to work outside of home, ability to take decision on household purchases and ability to take financial decisions. Column 5 combines all reported consumption from a detailed consumption module. The number of observations is low because many people did not know their consumption on at least one item. A disaggregated consumption analysis can be found in the appendix. The "Joint" row reports the p-value for the test for joint significance of the three treatment coefficients. The "Same" row reports the p-value for testing the hypotheses that there is no difference in the treatment coefficients. Heteroskedasticity-robust standard errors in parentheses. Regressions include cohort fixed effects. Significance * .10; ** .05; *** .01.

Table A7: Baseline Characteristics of top 25% at Endline vs. Rest of Sample

	Women			Men		
	Top 25% (1)	Bot 75% (2)	Diff (3)	Top 25% (4)	Bot 75% (5)	Diff (6)
All Participants						
Age	29.88	29.16	0.06	28.39	27.89	0.64
	(6.62)	(5.79)	(0.457)	(4.45)	(4.34)	(0.425)
College Education	0.11	0.07	0.02	0.14	0.11	0.03
	(0.31)	(0.26)	(0.020)	(0.35)	(0.31)	(0.027)
High School Education	0.51	0.57	-0.05	0.64	0.64	0.01
	(0.50)	(0.49)	(0.032)	(0.48)	(0.48)	(0.039)
Less than High School Education	0.36	0.32	0.03	0.18	0.22	-0.04
	(0.48)	(0.47)	(0.029)	(0.38)	(0.41)	(0.032)
Worked Before	0.17	0.21	0.01	0.43	0.48	0.05
	(0.37)	(0.41)	(0.023)	(0.50)	(0.50)	(0.030)
Has a business	0.07	0.10	0.00	0.14	0.14	-0.02
	(0.25)	(0.30)	(0.028)	(0.34)	(0.35)	(0.039)
Single	0.19	0.26	-0.02	0.55	0.60	0.01
	(0.39)	(0.44)	(0.031)	(0.50)	(0.49)	(0.039)
Married	0.73	0.70	-0.02	0.44	0.40	0.00
	(0.44)	(0.46)	(0.026)	(0.50)	(0.49)	(0.027)
Has kids	0.72	0.65	-0.01	0.38	0.32	0.02
	(0.45)	(0.48)	(0.018)	(0.49)	(0.47)	(0.027)
Low Family Income	0.37	0.31	0.03	0.29	0.25	0.04
	(0.48)	(0.46)	(0.022)	(0.46)	(0.43)	(0.026)
Has Previous Borrowing	0.14	0.10	0.03	0.13	0.10	-0.02
	(0.35)	(0.30)	(0.063)	(0.34)	(0.29)	(0.069)
External Pressure to Share Funds	0.08	0.00	0.015	0.00	0.02	0.05
	(1.00)	(1.02)	(0.032)	(0.94)	(0.95)	(0.038)
Joint P-val			0.306			0.000
N	467	1343		309	905	

Notes: Columns 1 and 4 represent the baseline characteristics of the people with the top 25% income at Endline. Columns 2 and 5 present the baseline characteristics for the rest of the sample. Columns 3 and 6 reports the difference between the two samples. Heteroskedasticity-robust standard errors in parentheses. Significance * .10; ** .05; *** .01.

Table A8: Different Types of Work

	Neither Wage nor Self Employment		Just Self Employment		Just Wage Employment		Both Wage and Self Employment	
	Female	Male	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Micro credit	-0.139***	0.006	0.121***	0.075**	0.007	-0.144***	0.011*	0.063***
	(0.027)	(0.022)	(0.023)	(0.031)	(0.017)	(0.036)	(0.006)	(0.022)
In kind grant	-0.202***	-0.015	0.217***	0.087**	-0.029	-0.136***	0.014*	0.065**
	(0.031)	(0.025)	(0.028)	(0.035)	(0.018)	(0.041)	(0.008)	(0.026)
Cash grant	-0.214***	0.000	0.193***	0.075**	-0.004	-0.114***	0.025***	0.039
	(0.030)	(0.025)	(0.027)	(0.036)	(0.019)	(0.041)	(0.009)	(0.025)
Mean	0.759	0.104	0.144	0.197	0.091	0.628	0.005	0.071
Joint significance of treatments	0.000	0.867	0.000	0.023	0.210	0.000	0.016	0.014
Same effect across treatments	0.035	0.699	0.003	0.941	0.121	0.765	0.377	0.593
N	1835	1240	1835	1240	1835	1240	1835	1240

Notes: This table reports the different type of working arrangements for participants in the sample split by gender. Each outcome is a binary indicator for if the person works in wage or self-employment, both, or neither. The "Joint" row reports the p-value for the test for joint significance of the three treatment coefficients. The "Same" row reports the p-value for testing the hypotheses that there is no difference in the treatment coefficients. Heteroskedasticity-robust standard errors in parentheses. Regressions include cohort fixed effects. Significance * .10; ** .05; *** .01.

Table A9: Testing Heterogeneity Within & Across Treatment Arms at Different Quantiles

	p-value
Panel A: Female Participants	
Quantile effects in each treatment arm are equal	<0.001
Quantile effects across treatment arms are equal	0.659
Panel B: Male Participants	
Quantile effects in each treatment arm are equal	0.501
Quantile effects across treatment arms are equal	0.448

Notes:This table reports p-values for three different types of test. The first is to test for heterogeniety within treatment arms. This is implemented by computing values $q \in \{.20, .30, .40, .50, .60, .70, .80, .90, .95\}$, and testing if $\beta_{.25,T} = ... = \beta_{.95,T}$ using wald tests with 10,000 bootstrap replications. Next it tests if treatment effects across arms are equal by testing if $\beta_{q,L} = \beta_{q,IK} = \beta_{q,C}$ in a similar fashion. Finally it tests if distributions are equivalent across arms by computing the sum of the absolute value of the three 2x2 ranksum statistics and computing its p-value using randomization inference with 10,000 permutations.

Table A10: Balance among bottom 25% of participants in each treatment group

	Mean in assignment groups				p-values	
	Control	Microcredit	In-Kind	Cash	3 treatment groups	4 assignment groups
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Female Participants						
Age	29.03	29.3	29.15	28.22	0.93	0.97
College Education	0.07	0.05	0.1	0.08	0.01	0.03
High School Education	0.66	0.59	0.59	0.66	0.15	0.38
Less than High School Education	0.26	0.31	0.28	0.22	0.73	0.74
Worked Before	1.75	1.7	1.66	1.69	0.47	0.52
Single	0.28	0.2	0.25	0.3	0.90	0.18
Married	0.68	0.8	0.69	0.65	0.78	0.90
Low Family Income	0.23	0.17	0.14	0.21	0.92	0.45
Has a Business	0.14	0.16	0.21	0.14	0.32	0.43
Any Borrowing	0.09	0.06	0.1	0.04	0.40	0.74
External Pressure to Share Funds	-0.02	0.1	0.17	0.00	0.14	0.12
Has Kids	0.64	0.73	0.64	0.61	0.73	0.87
Balancing test p-values					0.568	0.765
Panel B: Male Participants						
Age	28.49	27.94	27.82	28.83	0.76	0.94
College Education	0.14	0.16	0.15	0.10	0.05	0.14
High School Education	0.66	0.63	0.60	0.67	0.27	0.17
Less than High School Education	0.15	0.17	0.18	0.22	0.96	0.38
Worked Before	1.54	2.55	1.46	1.65	0.68	0.62
Single	0.56	0.55	0.63	0.45	0.57	0.37
Married	0.43	0.44	0.35	0.53	0.17	0.06
Low Family Income	0.29	0.31	0.27	0.31	0.42	0.32
Has a Business	0.14	0.14	0.13	0.12	0.97	0.59
Any Borrowing	0.12	0.12	0.18	0.12	0.14	0.26
External Pressure to Share Funds	-0.02	-0.03	0.07	-0.06	0.56	0.86
Has Kids	0.36	0.41	0.30	0.43	0.49	0.28
Balancing test p-values					0.827	0.379

The table presents the average of each characteristics for individuals in the top 75-100th percentile of total income at endline in each assignment group. Column 5 presents the p-value of the test of equality of means among all three treatment groups. Column 6 presents the p-value of the test of equality of means among all four assignment groups. The group p-values are listed at the bottom of each panel and are presents the results of the joint balancing test by computing the test statistic outlined in Gagnon-Bartsch et al. (2019).

Table A11: Balance among 25-50th percentile participants in each treatment group

	Mean in assignment groups				p-values	
	Control	Microcredit	In-Kind	Cash	3 treatment groups	4 assignment groups
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Female Participants						
Age	28.79	28.95	28.67	28.94	0.68	0.83
College Education	0.06	0.08	0.13	0.07	0.02	0.10
High School Education	0.60	0.67	0.59	0.57	0.12	0.30
Less than High School Education	0.30	0.23	0.27	0.36	0.77	0.64
Worked Before	1.87	1.79	1.87	1.83	0.45	0.50
Single	0.40	0.29	0.35	0.26	0.17	0.07
Married	0.58	0.69	0.63	0.68	0.40	0.66
Low Family Income	0.35	0.39	0.4	0.32	0.46	0.61
Has a Business	0.06	0.07	0.06	0.07	0.45	0.55
Any Borrowing	0.10	0.1	0.11	0.09	0.85	1.00
External Pressure to Share Funds	0.02	0.02	-0.05	-0.01	0.79	0.33
Has Kids	0.53	0.64	0.59	0.62	0.82	0.47
Balancing test p-values						
					0.029	0.012
Panel B: Male Participants						
Age	28.49	28.24	27.71	27.7	0.78	0.79
College Education	0.12	0.11	0.14	0.07	0.04	0.11
High School Education	0.61	0.68	0.64	0.76	0.29	0.21
Less than High School Education	0.26	0.17	0.19	0.15	0.91	0.54
Worked Before	1.49	1.58	1.57	1.54	0.97	0.22
Single	0.61	0.57	0.61	0.59	0.77	0.45
Married	0.38	0.43	0.39	0.41	0.58	0.10
Low Family Income	0.2	0.21	0.22	0.23	0.42	0.48
Has a Business	0.15	0.11	0.10	0.14	0.70	0.71
Any Borrowing	0.11	0.09	0.09	0.08	0.29	0.55
External Pressure to Share Funds	0.02	0.00	-0.17	-0.01	0.96	1.00
Has Kids	0.31	0.38	0.30	0.32	0.82	0.26
Balancing test p-values						
					0.767	0.508

The table presents the average of each characteristics for individuals in the top 25-50th percentile of total income at endline in each assignment group. Column 5 presents the p-value of the test of equality of means among all three treatment groups. Column 6 presents the p-value of the test of equality of means among all four assignment groups. The group p-values are listed at the bottom of each panel and are presents the results of the joint balancing test by computing the test statistic outlined in Gagnon-Bartsch et al. (2019).

Table A12: Balance among 50-75th percentile participants in each treatment group

	Mean in assignment groups				p-values	
	Control	Microcredit	In-Kind	Cash	3 treatment groups	4 assignment groups
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Female Participants						
Age	28.30	29.42	29.34	30.20	0.53	0.50
College Education	0.10	0.09	0.04	0.03	0.06	0.07
High School Education	0.46	0.52	0.46	0.44	0.22	0.48
Less than High School Education	0.38	0.36	0.47	0.48	0.86	0.47
Worked Before	1.81	1.82	1.88	1.81	0.46	0.53
Single	0.20	0.14	0.26	0.18	0.30	0.36
Married	0.71	0.78	0.65	0.75	0.22	0.29
Low Family Income	0.39	0.42	0.43	0.32	0.13	0.22
Has a Business	0.08	0.06	0.04	0.11	0.10	0.21
Any Borrowing	0.13	0.07	0.11	0.18	0.47	0.28
External Pressure to Share Funds	-0.11	-0.07	-0.01	0.20	0.64	0.25
Has Kids	0.68	0.74	0.67	0.75	0.92	0.38
Balancing test p-values						
					0.892	0.782
Panel B: Male Participants						
Age	27.91	28.05	28.29	28.54	0.96	0.99
College Education	0.08	0.12	0.1	0.12	0.13	0.26
High School Education	0.71	0.6	0.67	0.58	0.97	0.29
Less than High School Education	0.16	0.24	0.18	0.29	0.43	0.32
Worked Before	1.47	1.56	1.35	1.56	0.63	0.52
Single	0.57	0.53	0.47	0.53	0.58	0.24
Married	0.43	0.47	0.53	0.47	0.87	0.14
Low Family Income	0.27	0.24	0.29	0.25	0.30	0.54
Has a Business	0.19	0.24	0.1	0.07	0.92	0.12
Any Borrowing	0.12	0.06	0.16	0.14	0.32	0.14
External Pressure to Share Funds	0.11	-0.12	0.1	0.24	1.00	0.68
Has Kids	0.38	0.36	0.41	0.32	0.70	0.36
Balancing test p-values						
					0.928	0.632

The table presents the average of each characteristics for individuals in the top 50-75th percentile of total income at endline in each assignment group. Column 5 presents the p-value of the test of equality of means among all three treatment groups. Column 6 presents the p-value of the test of equality of means among all four assignment groups. The group p-values are listed at the bottom of each panel and are presents the results of the joint balancing test by computing the test statistic outlined in Gagnon-Bartsch et al. (2019).

Table A13: Heterogeneity Effect on Total Income (Women)

Treatment Interacted With:		Has Business (1)	Wants Business (2)	Saves Regularly (3)	Has Children (4)	Borrowed Before (5)	Share Extra Profit (6)	External Pressure (7)
Panel A: Female Participants								
Microcredit	Main	81.52**	84.48	60.39	213.00***	69.43*	84.12*	86.22**
		(36.91)	(49.66)	(52.35)	(57.71)	(35.59)	(45.61)	(35.07)
	Interaction	55.73	-12.90	-24.7	-185.00**	189.00*	2.75	-35.20
		(120.00)	(70.82)	(69.94)	(71.34)	(148.00)	(69.62)	(37.06)
In Kind	Main	145.00***	115.00*	239.00*	161.00**	163.00***	96.48*	154.00***
		(44.99)	(57.44)	(69.51)	(65.79)	(45.54)	(54.75)	(42.53)
	Interaction	147.00	56.36	-38.90	-115.40	-38.70	138.00	52.67
		(149.00)	(87.86)	(90.12)	(85.66)	(143.00)	(87.48)	(41.39)
Cash	Main	89.27***	114.00*	95.31*	192.00***	118.00***	17.29	93.60**
		(40.89)	(59.45)	(58.98)	(65.35)	(40.89)	(46.23)	(38.09)
	Interaction	73.49	-28.00	14.88	-144.70	-217.80	192.00**	44.66
		(113.00)	(80.89)	(79.82)	(81.62)	(114.00)	(80.59)	(40.55)
Control Mean		462	432	384	369	456	445	455
Proportion with Interaction Variable		0.09	0.55	0.65	0.67	0.11	0.42	0.03
P-value of Main effect		0.00	0.02	0.00	0.00	0.00	0.05	0.00
P-value of Interaction effect		0.53	0.66	0.69	0.07	0.20	0.08	0.63
N		1809	1756	1729	1809	1809	1809	1809

Notes: This table reports the impact on total income for each of the three treatment arms interacted with the variable listed at the top of the column. Column 7 is an index of questions on whether the individual says there is pressure to share extra profits with others, that whenever there is money on hand others request it, that people who do well in business receive additional request for money, that machines and equipment are a good way to save money so others don't take it, household size and marital status. Reported p-values comes from testing if the main effect estimates are jointly equal to 0, and from testing if the interaction effects are jointly equal to 0. Total income is winsorized at the 99th percentile. Heteroskedasticity-robust standard errors in parentheses. Regressions include cohort fixed effects. Significance * .10; ** .05; *** .01.

Table A14: Heterogeneity Effect on Total Income (Men)

	Treatment Interacted With:	Has Business (1)	Wants Business (2)	Saves Regularly (3)	Has Children (4)	Borrowed Before (5)	Share Extra Profit (6)	External Pressure (7)
Panel B: Male Participants								
Microcredit	Main	84.47	-34.80	43.40	17.69	56.71	-32.50	50.10
		(107.00)	(138.00)	(176.00)	(130.00)	(111.00)	(154.00)	(109.00)
	Interaction	-176.00	130.00	-14.40	74.81	2.31	169.00	85.40
		(365.00)	(215.00)	(227.00)	(245.00)	(432.00)	(217.00)	(110.00)
In Kind	Main	49.65	208.00	226.00	138.00	29.78	-191.00	31.71
		(120.00)	(198.00)	(227.00)	(163.00)	(132.00)	(151.00)	(124.00)
	Interaction	33.75	-357.00	-355.00	-312.00	105.00	460.00*	71.30
		(506.00)	(252.00)	(263.00)	(242.00)	(366.00)	(245.00)	(134.00)
Cash	Main	79.63	170.00	51.14	-17.10	18.36	-74.30	-25.40
		(119.00)	(180.00)	(242.00)	(146.00)	(123.00)	(165.00)	(116.00)
	Interaction	-739.00*	-348.00	-133.00	-18.80	-381.00	96.83	-13.30
		(371.00)	(243.00)	(279.00)	(245.00)	(353.00)	(236.00)	(113.00)
Control Mean		1660	1730	1700	1680	1690	1770	1730
Proportion with Interaction Variable		0.14	0.51	0.64	0.34	0.10	0.48	0.00
P-value of Main effect		0.44	0.58	0.56	0.77	0.74	0.46	0.82
P-value of Interaction effect		0.43	0.54	0.48	0.85	0.90	0.19	0.46
N		1209	1181	1164	1209	1209	1209	1209

Notes: Table reports the impact on total income for each of the three treatment arms interacted with the variable listed at the top of the column. Column 7 is an index of questions on whether the individual says there is pressure to share extra profits with others, that whenever there is money on hand others request it, that people who do well in business receive additional request for money, that machines and equipment are a good way to save money so others don't take it, household size and marital status. Reported p-values comes from testing if the main effect estimates are jointly equal to 0, and from testing if the interaction effects are jointly equal to 0. Total income is winsorized at the 99th percentile. Heteroskedasticity-robust standard errors in parentheses. Regressions include cohort fixed effects. Significance * .10; ** .05; *** .01.

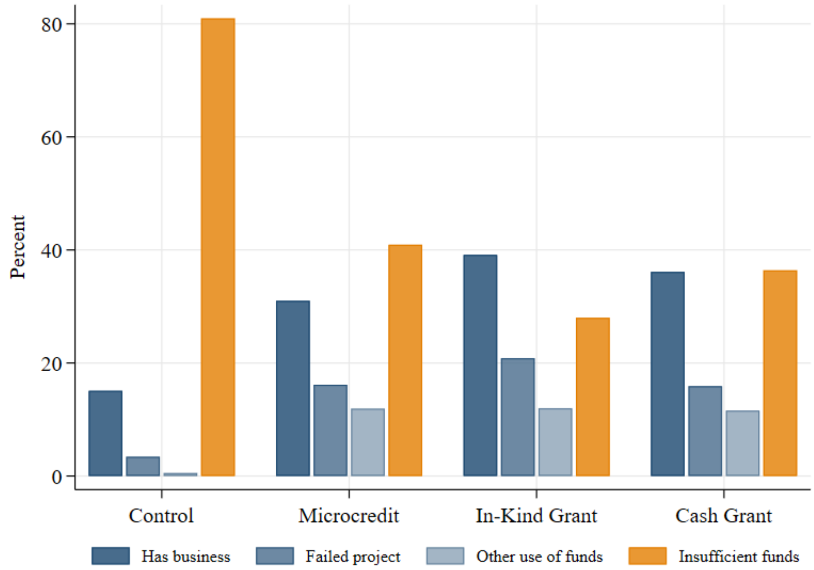
Table A15: Utilization of Financial Instruments

	Borrowing Info Including Experiment Loan								
	Any External Loan (1)	Formal Loan (2)	Informal Loan (3)	Rosca Credit (4)	Total External Loans (5)	Total Loans (6)	Rosca Savings (7)	Personl Savings (8)	Fin In (
Panel A: Female Participants									
Micro credit	0.216***	723.128***	6.071	43.846	773.045***	2837.235***	33.906	33.403	0.18
	(0.029)	(131.368)	(87.255)	(41.025)	(167.609)	(175.362)	(37.522)	(24.681)	(0.0
In kind grant	0.021	82.890	219.232	-34.946	267.176	272.877	167.958**	78.977**	0.23
	(0.033)	(150.364)	(133.840)	(29.688)	(218.465)	(218.981)	(71.727)	(33.741)	(0.0
Cash grant	0.026	-90.080	249.513**	-63.723**	95.709	90.929	80.339	70.647**	0.1
	(0.032)	(142.480)	(125.282)	(27.063)	(201.591)	(201.690)	(54.720)	(29.215)	(0.0
Mean	0.378	876.916	457.959	108.449	1443.324	1443.324	97.237	55.927	0.0
Joint significance of treatments	0.000	0.000	0.098	0.006	0.000	0.000	0.091	0.025	0.0
Same effect across treatments	0.000	0.000	0.087	0.009	0.002	0.000	0.182	0.344	0.3
N	1835	1835	1835	1835	1835	1835	1835	1834	18
Panel B: Male Participants									
Micro credit	0.164***	280.424	-365.252	-150.627**	-235.455	1878.747***	-53.414	201.524	-0.
	(0.036)	(237.485)	(240.210)	(63.950)	(356.526)	(360.381)	(100.296)	(205.702)	(0.0
In kind grant	0.037	-229.743	178.587	-8.029	-59.185	-62.152	-101.385	258.544	-0.
	(0.042)	(265.855)	(346.094)	(74.538)	(442.935)	(443.233)	(85.756)	(261.106)	(0.0
Cash grant	-0.019	-218.746	-448.213*	-45.383	-712.342*	-712.696*	6.944	337.228	-0.
	(0.042)	(276.356)	(258.286)	(99.885)	(402.127)	(402.076)	(115.085)	(339.285)	(0.0
Mean	0.440	1591.530	1239.809	206.448	3037.787	3037.787	256.967	676.621	0.0
Joint significance of treatments	0.000	0.095	0.096	0.008	0.275	0.000	0.554	0.616	0.7
Same effect across treatments	0.000	0.041	0.130	0.014	0.241	0.000	0.526	0.916	0.7
N	1240	1240	1240	1240	1240	1240	1240	1230	12

Notes: Column 1 is a binary variable that is equal to 1 if the individual took any loan from a bank, an MFI, family member or through ROSCA other than the experi loan. Column 2 reports size of the loans taken from formal entities including the experiment loan that was wrongly reported as outside loans. Column 3 reports the loa family. Column 4 is the amount still left to be paid to a Rosca at the time of the survey. Column 5 is the total of loans taken from a bank, an MFI, family member or thr ROSCA. Column 6 adds to the total to the experiment loan. Column 7 is the amount paid into Rosca's at the time of the survey. Column 9 is a standardized index of co 2,3,4,7,8. Amounts are winsorized at the 99th percentile. The "Joint" row reports the p-value for the test for joint significance of the three treatment coefficients. The " row reports the p-value for testing the hypotheses that there is no difference in the treatment coefficients. Heteroskedasticity-robust standard errors in parentheses. Regre include cohort fixed effects. Significance * .10; ** .05; *** .01.

Figure A1: Why No Project Was Implemented

Female



Male

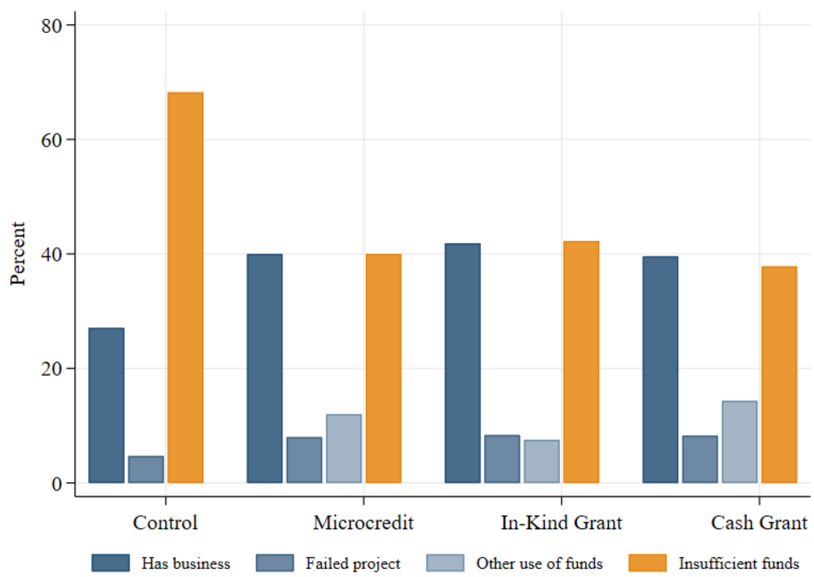
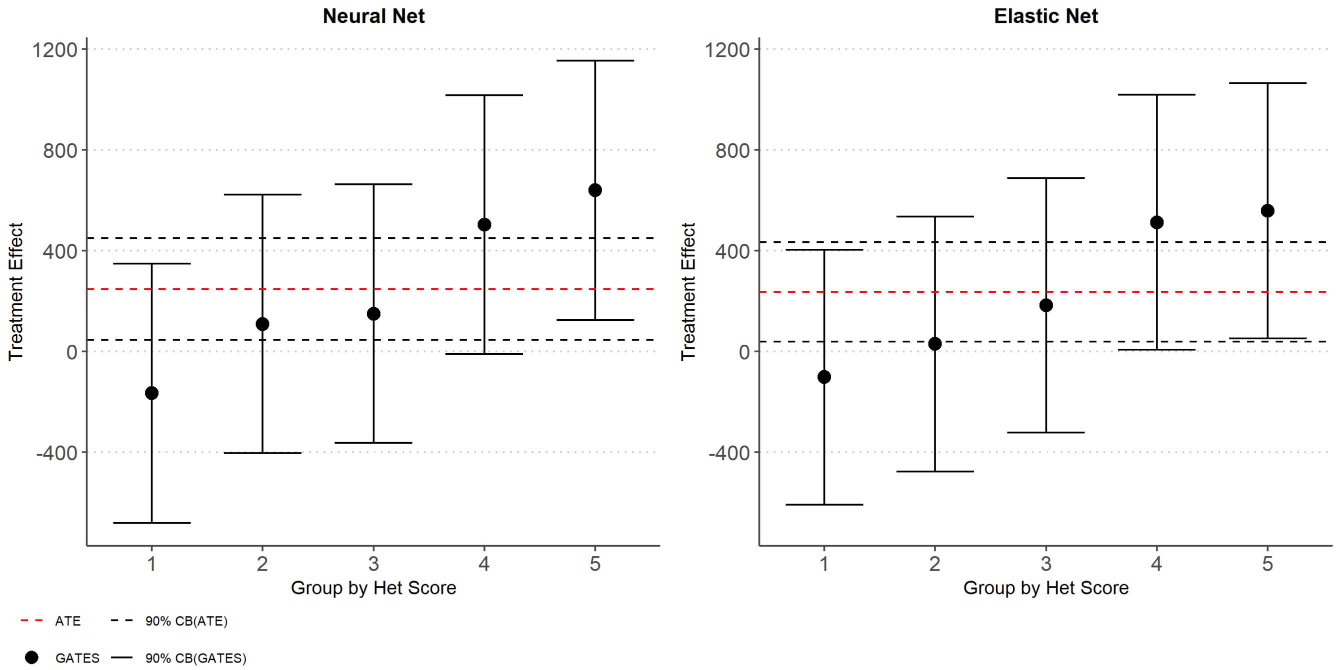
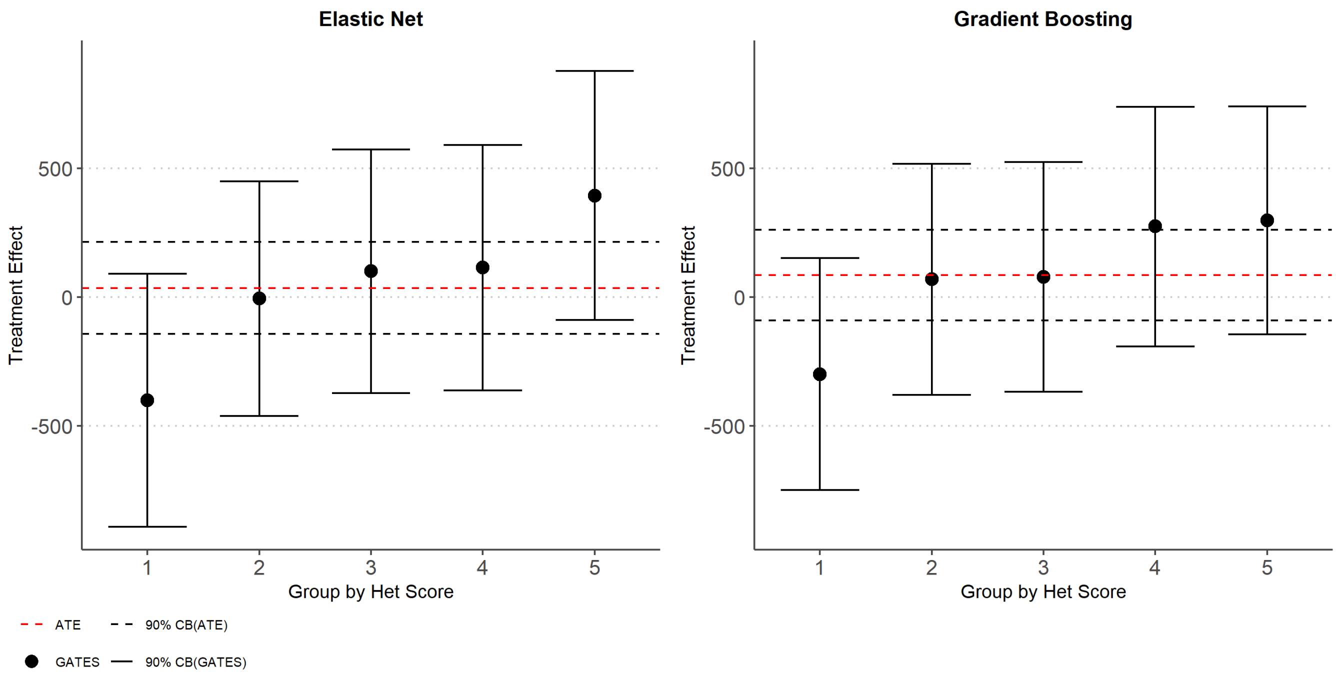


Figure A2: Heterogeneity Predicted Using Machine Learning Methods

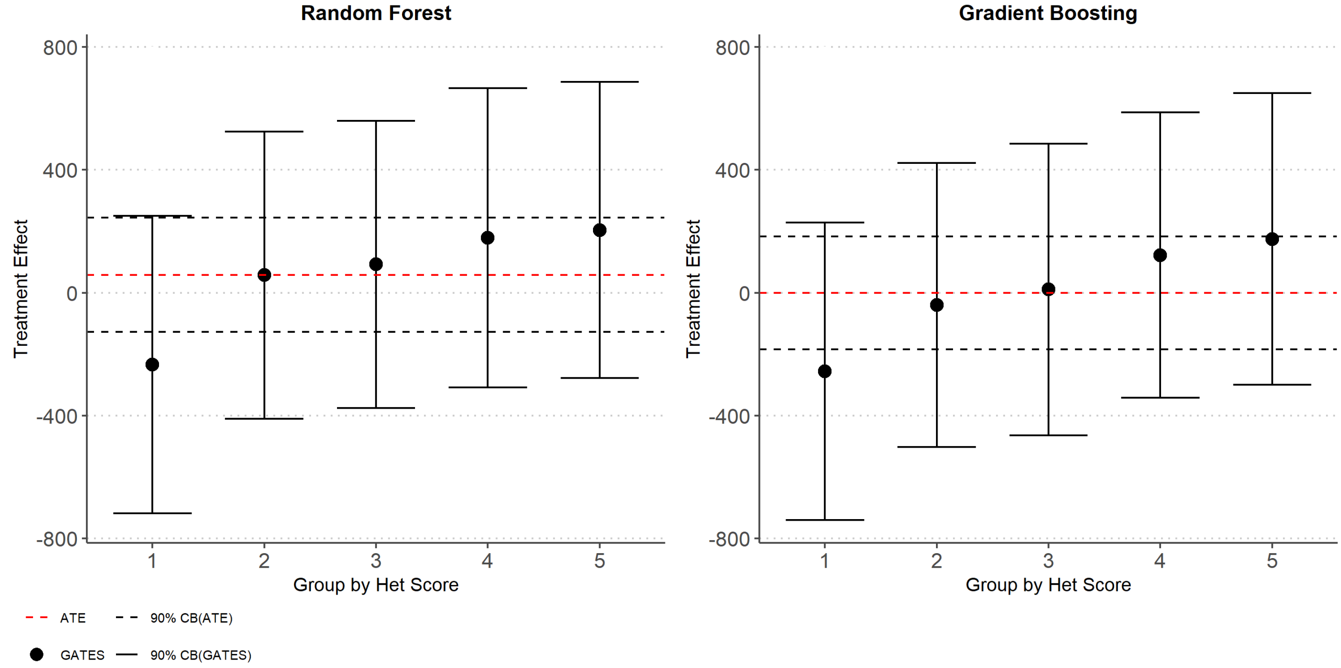
Control vs. Microcredit



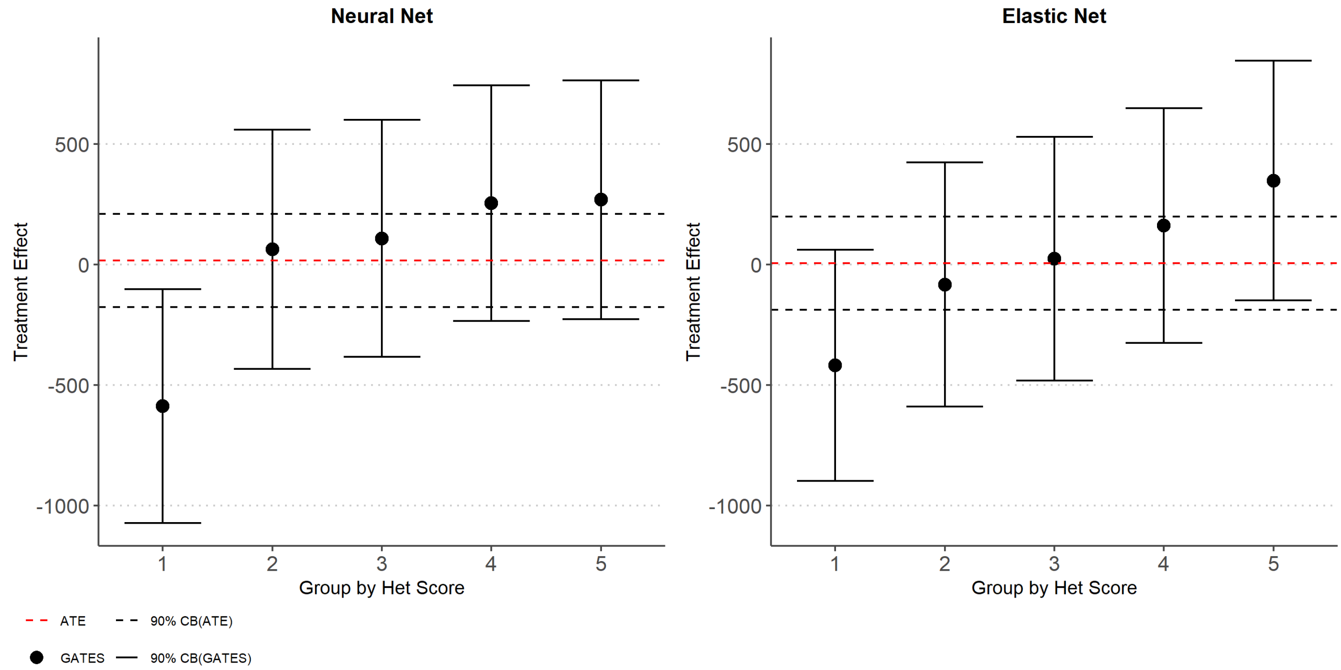
Control vs. In Kind Grant



Control vs. Cash Grant



Control vs. all



Appendix B: Robustness Checks

Table B1: Double Post Lasso on All Participants

	Has Business (1)	Profits (2)	Wage (3)	Has Work (4)	Labor Income (5)	Total Income (6)
Micro credit	0.117***	47.822	5.238	0.091***	59.031	44.400
	(0.027)	(56.088)	(39.767)	(0.028)	(61.037)	(65.324)
In kind grant	0.198***	58.870	-35.748	0.150***	25.473	76.655
	(0.031)	(50.977)	(45.664)	(0.032)	(57.535)	(66.821)
Cash grant	0.232***	102.115**	-49.121	0.156***	56.066	62.547
	(0.031)	(49.494)	(42.106)	(0.030)	(53.998)	(59.857)
Baseline Variables Selected						
Household owns landline phone	-0.002***	-4.208***	-12.797***	-0.008***	-16.036***	-20.370***
	(0.001)	(0.795)	(1.690)	(0.001)	(1.517)	(1.728)
Gender (Male)		475.612***	903.692***	0.501***	1450.561***	1194.734***
		(40.701)	(37.275)	(0.016)	(44.726)	(44.851)
Household owns auto wash machine		160.071***			163.613***	173.817***
		(38.916)			(42.666)	(44.066)
Husband with less than High School Education			-123.425***		-55.230	
			(25.443)		(35.035)	
Husband with High School Education			-67.688***			
			(23.126)			
Q5 of Work Income			172.845***	0.067***		
			(50.802)	(0.023)		
Less than High School Education					-187.644***	-209.854***
					(55.374)	(59.055)
Q5 of working days					85.126	117.363
					(84.416)	(85.199)
Constant	0.176	-5.613	-12.807	0.263**	-47.757	-0.690
	(0.145)	(111.655)	(115.125)	(0.131)	(78.339)	(78.254)
N	1524	1522	1524	1524	1522	1522

Notes: This table replicates the regressions on key variables using a double-post-lasso procedure to choose control variables. The bottom panel shows which controls were chosen by the procedure. Standard errors in parentheses.Regressions include cohort fixed effects. Significance * .10; ** .05; *** .01.

Table B2: Double Post Lasso on Women

	Has Business (1)	Profits (2)	Wage (3)	Has Work (4)	Labor Income (5)	Total Income (6)
Micro credit	0.112***	27.842	-4.831	0.099***	23.362	5.896
	(0.030)	(19.802)	(17.306)	(0.033)	(25.923)	(43.671)
In kind grant	0.231***	101.908***	-19.127	0.196***	82.550**	142.208**
	(0.036)	(32.507)	(17.904)	(0.038)	(36.568)	(62.172)
Cash grant	0.236***	68.161***	-1.500	0.199***	66.588**	62.697
	(0.034)	(20.225)	(19.660)	(0.037)	(29.704)	(47.451)
Baseline Variables Selected						
Q5 if working days (Micro credit only)	0.015	6.823	23.855	0.030	23.728	30.817
	(0.037)	(33.539)	(33.027)	(0.042)	(45.939)	(54.950)
Less than High School Education			-53.646***			
			(13.475)			
Has Kids			-71.900***			
			(18.454)			
Husband with less than High School Education			-36.173***			
			(13.355)			
Single				0.109***		
				(0.027)		
Household has dirt floor					-91.812***	
					(21.441)	
Constant	0.164	5.396	0.768	0.176	6.029	-1.905
	(0.185)	(43.415)	(12.875)	(0.183)	(44.778)	(57.133)
N	1131	1131	1131	1131	1131	1131

Notes: This table replicates the regressions on key variables using a double-post-lasso procedure to choose control variables. The bottom panel shows which controls were chosen by the procedure. Standard errors in parentheses.Regressions include cohort fixed effects. Significance * .10; ** .05; *** .01.

Table B3: Double Post Lasso on Men

	Has Business	Profits	Wage	Has Work	Labor Income	Total Income
	(1)	(2)	(3)	(4)	(5)	(6)
Micro credit	0.119**	64.121	-65.593	-0.014	28.842	79.978
	(0.057)	(206.278)	(134.683)	(0.037)	(208.302)	(207.658)
In kind grant	0.102	-112.295	-92.766	0.015	-240.544	-237.683
	(0.067)	(176.129)	(159.600)	(0.044)	(181.703)	(180.696)
Cash grant	0.229***	185.359	-213.485	0.044	33.510	37.445
	(0.069)	(194.285)	(153.040)	(0.038)	(191.674)	(190.925)
Baseline Variables Selected						
Household owns landline phone				-0.011***		
				(0.000)		
Household owns auto wash machine					-609.303***	-624.926***
					(151.999)	(151.195)
Constant	0.217	316.840	959.693***	1.011***	2261.388***	2269.069***
	(0.230)	(306.692)	(341.695)	(0.026)	(254.928)	(255.615)
N	1160	1156	1159	1160	1155	1155

Notes: This table replicates the regressions on key variables using a double-post-lasso procedure to choose control variables. The bottom panel shows which controls were chosen by the procedure. Standard errors in parentheses.Regressions include cohort fixed effects. Significance * .10; ** .05; *** .01.

Table B4: Lee Bounds for Primary Outcomes

	Total Loans (1)	Has Business (2)	New Assets (3)	Monthly Profits (4)	Has Work (5)	Labor Income (6)	Total Income (7)	Quality of Life (8)
All Participants								
Lower Bound	-1158***	0.119***	-1100***	-123***	0.086***	-170***	-136***	-0.181*
	(205)	(0.019)	(303)	(32)	(0.021)	(51)	(50)	(0.098)
Upper Bound	155	0.202***	926**	128***	0.169***	162***	205***	0.473***
	(203)	(0.018)	(374)	(36)	(0.022)	(49)	(49)	(0.097)
N	3293	3293	3293	3293	3293	3293	3293	3293
Female Participants								
Lower Bound	-846***	0.108***	-199***	-22*	0.111***	-47***	-76**	-0.309**
	(169)	(0.026)	(49)	(11)	(0.027)	(17)	(34)	(0.127)
Upper Bound	706***	0.241***	535***	98***	0.244***	136***	212***	0.655***
	(199)	(0.023)	(89)	(15)	(0.026)	(22)	(35)	(0.136)
N	2053	2053	2053	2053	2053	2053	2053	2053
Male Participants								
Lower Bound	-2599***	0.013	-3035***	-373***	-0.023	-458***	-437***	-0.429***
	(396)	(0.037)	(739)	(75)	(0.021)	(90)	(92)	(0.144)
Upper Bound	-271	0.215***	2017**	242***	0.104***	357***	371***	0.706***
	(429)	(0.033)	(970)	(90)	(0.016)	(102)	(100)	(0.167)
N	1458	1458	1458	1458	1458	1458	1458	1458

Notes: This table replicates the regressions on key variables using a Lee bounds to account for attrition. Standard errors in parentheses.Regressions include cohort fixed effects. Significance * .10; ** .05; *** .01.

Appendix C: Estimating the Cost Effectiveness of the Interventions

To assess the cost effectiveness of the different interventions we collected detailed data on the actual costs incurred by the funder and implementers. We utilize those data with a simple framework detailed below to estimate the overall costs of each intrevention and compare it to the benefits estimated from the experiment.

Loans

We consider a loan of size C. From the NGO side there are two costs, one corresponds to the capital cost $S(C)$. Because the loan is subsidized this cost can be written as

$$S(C) = C - \sum_{k=0}^{T_L} \beta^k R_k(C) = s^L C \tag{C1}$$

There is also the implementation, or management cost, $M(C) = mC$, corresponding to all effort and interactions with participants, from delivering the loan, to explaining the rules, efforts to get the loan repaid and losses in case of default.[27] Thus the total cost of the loan is

$$Cost^L(C) = S(C) + M^L(C) = (s^L + m)C \tag{C2}$$

The cost data (see table C1) shows that, aggregated over the three NGOs, the management cost of providing the capital assistance, including salaries of loan officers and administrative cost, assets and training is $m = 1238460/5046400 = 0.245$. This management cost is the same for loan and grants.

When considering impacts on income, a loan of size C generates a flow of additional income $\pi_k^L(C)$. It also requires from the participant to pay back the loan. This leads to reimbursement flows $R_k(C)$ which stops after the duration of the loan T_L. We consider that

[27] Note that normally the cost of loans would include the cost of expected default. There was no loan default in our sample. Default is extremely rare in this context because Egypt's legal system allows creditors to send debtors who are unable to pay back their debt to prison. Before the start of this project we included in the agreement with the implementing partners that anyone who defaults on the loan would have their debt automatically forgiven. This was not communicated with the participants to avoid issues of moral hazard. In the end this clause did not have to be used. In other contexts where default is more common, the cost of the loan could increase by up to 0.1C (assuming 10% default), which would make a grant 2.8X more expensive than a loan instead of 3.65X more expensive.

the discounted rate is β and make the assumption that it is the same for the NGO and the borrower. The net value of the project for the participant over these T period is then

$$V^L(C) = \sum_{k=0}^{\infty} \beta^k \pi_k^L(C) - \sum_{k=0}^{T_L} \beta^k R_k(C) \tag{C3}$$

We consider $\beta = 1/(1+r)$ with r chosen so that the implied annual rate is 15% which leads to r$=$ 1.17% and $\beta = 0.988$.

We assume a "sudden death" model in which profits generated by the project are constant over time up to a period D where they become zero. We also assume a linear relation between profit and capital, so that $\pi_k^L(C) = \pi^L C 1(k \leq D)$. On reimbursement side, we assume that the loans are subsidized so that the discounted value of total reimbursement is $(1 - s^L)C$. Our discussions with the partner lead to consider that $s^L = 0.1$.

Given all these assumptions, the net value of the project for the borrower simply writes as

$$V^L(C) = \left(\frac{1-\beta^D}{1-\beta} \pi^L - (1 - s^L) \right) C \tag{C4}$$

The global value of the project aggregating borrower net present value and the partner's cost is:

$$V_G^L(C) = \left(\frac{1-\beta^D}{1-\beta} \pi^L - (1 + m) \right) C \tag{C5}$$

To compute the break-even date, the duration impacts on income have to be sustained for the intervention to pay for itself, we calculate

$$D = log\left(1 - \frac{1+m}{\pi^L}(1-\beta)\right) / log(\beta) \tag{C6}$$

Next we compute the benefit to cost ratio assuming a specific duration D in months

$$(B/Cost)_L = \frac{\frac{1-\beta^D}{1-\beta}\pi^L - (1 - s^L)}{s^L + m} \tag{C7}$$

<u>Grants</u>

For the grants we have exactly the same types of equations except there is no reimbursement and there is a full subsidy: $s^G = 1$. This does not affect the expression of the break-even date and gives for the benefit to cost ratio

$$(B/Cost)_G = \frac{\frac{1-\beta^D}{1-\beta}\pi^G}{1+m} \tag{C8}$$

Length of Time Income Increases are Sustained

We only have one point of time in which we are able to estimate the impacts of income. For this reason, we need to assume that the income increases are generated at disbursement and stay constant until a specified date. As we describe in section 5 and Table C2 we find that the number of months that the income increase needs to be sustained to cover the costs of the program ranges from 17.8 to 26.9 for women.

Several papers in the literature are able to look at how income reacts over time in response to capital support. In De Mel et al. (2009) they collect data 2 years after the capital drop and find that the effects are sustained. Blattman et al. (2020) shows returns to grants being sustained at 4 years but then fading over a 9 year time horizon. This decrease is primarily due to the control group "catching up" as opposed to a drop back down from the treatment group. These estimates imply that we could expect that our impacts are sustained over the time range needed to achieve cost effectiveness.

Table C1: Management cost and disbursement

Management costs		Disbursement	Number	Amount
Salaries of project employees	477,200	Loan	1,004	2,173,000
Admin costs	83,000	Grants	1,241	2,873,400
Training and implementation	632,310			
Assets	45,950			
Total management cost	1,238,460	Total disbursement	2,245	5,046,400

Table C2: Elements of Cost Benefit Analysis

	$\frac{\partial TotalIncome}{\partial Capital}$	Months to cover cost	Benefit/Cost Ratio 30 months	40 months
	(1)	(2)	(3)	(4)
Panel A: Female Participants				
Microcredit	0.054***	26.9**	1.48	2.94
	(0.019)	(11.4)	(1.99)	(2.52)
In Kind	0.077***	17.8***	1.57***	1.99***
	(0.020)	(5.3)	(0.42)	(0.53)
Cash	0.056***	25.6***	1.14***	1.44***
	(0.018)	(9.6)	(0.36)	(0.46)
Joint significance of treatments	0.000	0.002	0.000	0.000
Same effect across treatments	0.550	0.590	0.652	0.568
N	1835	1835	1835	1835
Panel B: Male Participants				
Microcredit	0.040	38.5	0.06	1.15
	(0.051)	(62.7)	(5.34)	(6.74)
In Kind	0.019	123.7	0.39	0.49
	(0.051)	(743.3)	(1.04)	(1.31)
Cash	0.004	988.5	0.07	0.09
	(0.049)	(.)	(0.99)	(1.25)
Joint significance of treatments	0.872	0.827	0.984	0.985
Same effect across treatments	0.802	0.000	0.964	0.953
N	1240	1240	1240	1240

Notes: Column 1 reports the marginal impact of additional capital on labor income. Column 2 reports the months needed for additional earned income to equal cost of implementation. Columns 3 & 4 provide the benefit cost ratio assuming the impacts are sustained for 30 & 40 months respectively. The "Joint" row reports the p-value for the test for joint significance of the three treatment coefficients. The "Same" row reports the p-value for testing the hypotheses that there is no difference in the treatment coefficients. Heteroskedasticity-robust standard errors in parentheses. Regressions include cohort fixed effects. Significance * .10; ** .05; *** .01.

Appendix D: Combined Sample

Table D1: Compliance with the experimental protocol

	Amount Received	Received			Conditional Amount
		Micro Loan	In-Kind Grant	Cash Grant	
	(1)	(2)	(3)	(4)	(5)
Micro credit	2036	0.874	0.000	0.000	2331
In kind grant	2386	0.000	0.989	0.000	2414
Cash grant	2348	0.000	0.000	0.974	2410
Control	0.000	0.000	0.000	0.000	0.000
Observations	3293	3293	3293	3293	2116

Notes: The table uses administrative data received from implementing NGOs based on actual amounts disbursed to each individual in the study. Column 5 reports the amount of capital received conditional on receiving the loan/grant.

Table D2: Access to other financial instruments

	Borrowing Info Excluding Experiment Loan							
	Any External Loan (1)	Formal Loan (2)	Informal Loan (3)	Rosca Credit (4)	Total External Loans (5)	Total Loans (6)	Rosca Savings (7)	Perso Savin (8)
All Participants								
Micro credit	0.192***	-125.600	-128.944	-39.204	-293.749*	1791.024***	4.962	108.0
	(0.022)	(113.590)	(110.920)	(34.862)	(168.944)	(171.761)	(45.800)	(87.33
In kind grant	0.020	-7.783	176.584	-25.240	143.561	146.750	64.252	153.6
	(0.026)	(136.672)	(158.360)	(35.178)	(219.662)	(219.883)	(54.601)	(104.9
Cash grant	0.003	-171.281	-44.409	-51.390	-267.080	-267.508	48.307	178.6
	(0.026)	(131.209)	(126.966)	(41.353)	(196.050)	(196.165)	(56.914)	(131.8
Mean	0.402	1114.833	766.650	147.141	2028.625	2028.625	160.302	300.1
Joint significance of treatments	0.000	0.458	0.176	0.594	0.081	0.000	0.570	0.31
Same effect across treatments	0.000	0.490	0.102	0.777	0.085	0.000	0.496	0.84
N	3075	3075	3075	3075	3075	3075	3075	306

Notes: Column 1 is a binary variable that is equal to 1 if the individual took any loan from a bank, an MFI, family member or through ROSCA (other than the experiment 2 and 3 report the size of the loans taken from formal entities or from family. Column 4 is the amount paid into Rosca's at the time of the survey. Column 5 is the total of a bank, an MFI, family member or through ROSCA. Column 6 is the total of loans taken from a bank, an MFI, family member or through ROSCA in addition to the Column 7 is the amount still left to be paid to a Rosca at the time of the survey. Column 9 is a standardized index of columns 2,3,4,7,8. Amounts are winsorized at the The "Joint" row reports the p-value for the test for joint significance of the three treatment coefficients. The "Same" row reports the p-value for testing the hypotheses difference in the treatment coefficients. Heteroskedasticity-robust standard errors in parentheses. Regressions include cohort fixed effects. Significance * .10; ** .05; *** .

Table D3: Business activity

	Has Business	New Asset	Revenue	Expenditure	Profit	Total External Funding	Business Index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel B:All Participants							
Micro credit	0.140***	935.821**	660.043**	451.618*	110.837**	1809.562***	0.290***
	(0.020)	(462.009)	(304.772)	(271.227)	(45.036)	(237.135)	(0.059)
In kind grant	0.204***	150.839	306.340	222.350	125.952***	2841.045***	0.423***
	(0.023)	(381.376)	(219.814)	(197.400)	(48.835)	(304.442)	(0.074)
Cash grant	0.180***	921.872*	225.217	6.495	60.327	2205.575***	0.311***
	(0.023)	(541.899)	(218.066)	(184.910)	(42.219)	(289.829)	(0.061)
Mean	0.196	1453	1032	857	237	2785	0.000
Joint significance of treatments	0.000	0.092	0.165	0.233	0.025	0.000	0.000
Same effect across treatments	0.023	0.104	0.356	0.169	0.368	0.002	0.250
N	3075	3075	3071	3063	3070	3075	3075

Notes: Column 2 are assets bought during the year after randomization. Assets include business premises, land, furniture, equipment, and vehicles.Column 6 is the total of loans taken from a bank, an MFI, family member or through ROSCA in addition to the experiment loan or grant. Column 7 is an index of columns 1,2,3,4,5. Amounts are winsorized at the 99th percentile. The "Joint" row reports the p-value for the test for joint significance of the three treatment coefficients. The "Same" row reports the p-value for testing the hypotheses that there is no difference in the treatment coefficients. Heteroskedasticity-robust standard errors in parentheses. Regressions include cohort fixed effects. Significance * .10; ** .05; *** .01.

Table D4: Income

	Has Work (1)	Self Employment (2)	Wage Employment (3)	Labor Income (4)	Family Transfers (5)	Go Trans (6
All Participants						
Micro credit	0.098***	110.837**	-7.393	110.542*	-7.777	9.1
	(0.022)	(45.036)	(39.742)	(57.261)	(15.300)	(8.7
In kind grant	0.141***	125.952***	-8.510	116.793*	22.069	6.2
	(0.025)	(48.835)	(45.997)	(64.079)	(20.564)	(10.0
Cash grant	0.125***	60.327	-6.121	55.644	-3.108	13.8
	(0.025)	(42.219)	(45.079)	(59.489)	(17.719)	(9.9
Mean	0.499	237	491	729	111	10
Joint significance of treatments	0.000	0.025	0.997	0.161	0.532	0.5
Same effect across treatments	0.190	0.368	0.999	0.602	0.333	0.7
N	3075	3070	3074	3069	3075	307

Notes: Column 4 is the total of columns 2 and 3. Column 7 is the total of columns 2, 3, 5 and 6. Amounts are win percentile. The "Joint" row reports the p-value for the test for joint significance of the three treatment coefficients. The the p-value for testing the hypotheses that there is no difference in the treatment coefficients. Heteroskedasticity-robus parentheses. Regressions include cohort fixed effects. Significance * .10; ** .05; *** .01.

Table D5: Time Use

	Hours as					
	Employee	Self-employee	Home Agri.	Childcare	Household Chores	Econ -use I
	(1)	(2)	(3)	(4)	(5)	(6
All Participants						
Micro credit	-1.014	5.859***	0.412	-1.496	-3.531***	0.20
	(1.090)	(1.083)	(0.320)	(0.914)	(1.225)	(0.0
In kind grant	-0.947	7.549***	0.592	-1.566	-4.729***	0.29
	(1.250)	(1.218)	(0.415)	(1.037)	(1.354)	(0.0
Cash grant	-1.416	6.986***	0.546	-1.697*	-2.614*	0.28
	(1.206)	(1.220)	(0.382)	(1.015)	(1.377)	(0.0
Mean	15.381	8.910	2.269	10.822	20.382	0.0
Joint significance of treatments	0.659	0.000	0.350	0.260	0.003	0.0
Same effect across treatments	0.926	0.402	0.880	0.979	0.334	0.3
N	3075	3075	2258	2260	3075	30

Notes: This table reports weekly hours spent on each activity. Column 5 includes hours spent in the household on cl maintenance and gathering water or fuel. Column 6 is an index of columns 1,2,3. Hours are winsorized at the 99th per The "Joint" row reports the p-value for the test for joint significance of the three treatment coefficients. The "Same" row the p-value for testing the hypotheses that there is no difference in the treatment coefficients. Heteroskedasticity-robust st errors in parentheses. Regressions include cohort fixed effects. Significance * .10; ** .05; *** .01.

Table D6: Kolmogorov Smirnov tests

	Test groups vs Control			Among test groups		
	Loan	In-Kind	Cash	Loan/In-Kind	In-Kind/Cash	Cash/Loan
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Monthly Income						
All participants	0.001	0.000	0.006	0.767	0.312	0.313
Female participants	0.000	0.000	0.000	0.293	0.858	0.873
Male participants	0.730	0.982	0.762	0.480	0.424	0.556
Panel B: Monthly Profit						
All participants	0.000	0.000	0.000	0.088	0.256	0.911
Female participants	0.000	0.000	0.000	0.040	0.320	0.569
Male participants	0.029	0.014	0.080	0.998	1.000	1.000

Table reports the p-value from Kolmogorov Smirnov distributional tests of monthly income in panel A and monthly profits in panel B. Columns 1, 2, and 3 compare the distribution of income in each treatment arm to control. Column 4 compares the loan group to the in-kind group, Column 5 compares the in-kind group to the cash group and Column 6 compares the cash group to the loan group.

Figure D1: Capital Assistance Received

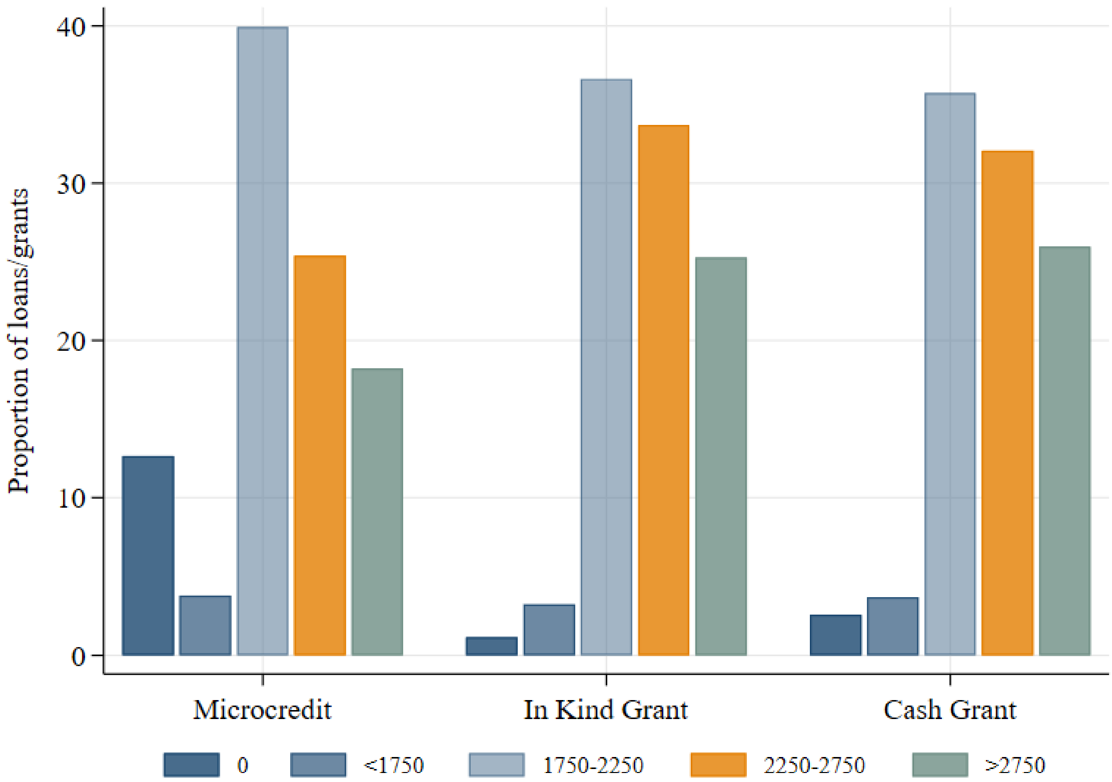


Figure D2: Why No Project Was Implemented

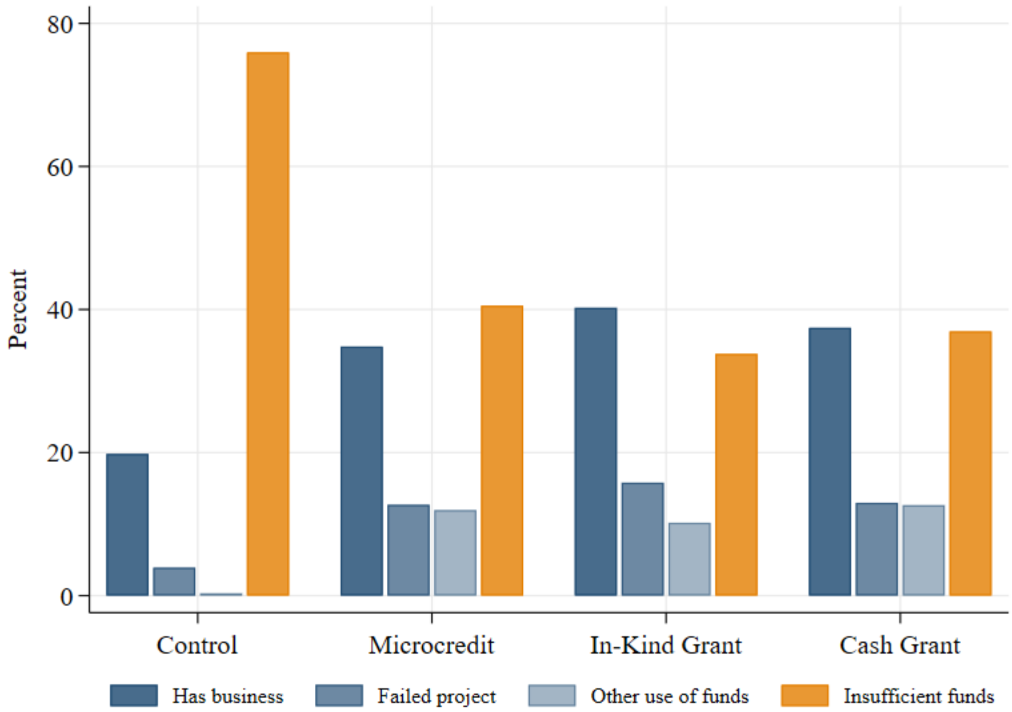
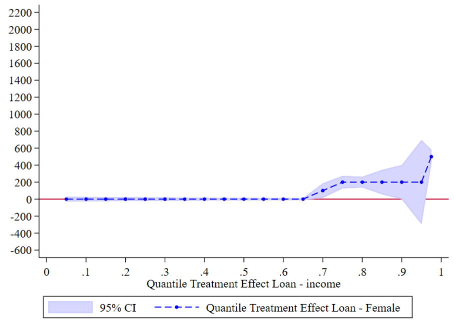
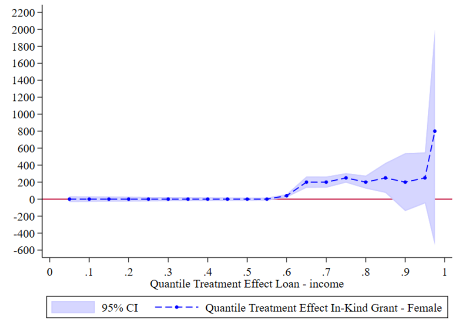
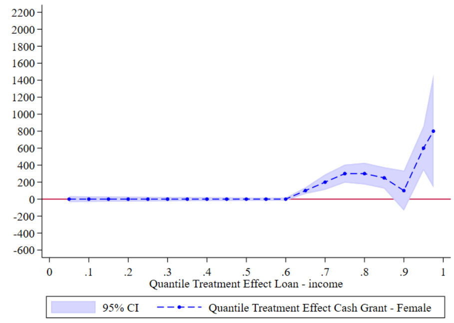


Figure D3: Quantile Treatment Effects for Total Income (All Participants)

Microcredit	In Kind Grant	Cash Grant
Loan		
		

Appendix E:
Multiple Hypothesis Testing

In this Appendix section we recreate our main tables but include sharpened q-values for each of the estimated treatment effects following the method put forth in Benjamini et al. (2006), and the code shared from Anderson (2008).

Table E1: Utilization of Financial Instruments

	Any External Loan (1)	Total External Loans (2)	Total Funding (3)	Total Savings (4)
Panel A: Female Participants				
Micro credit	0.216***	92.529	2244.872***	67.349
	(0.029)	(156.532)	(207.106)	(48.910)
	<0.001>	<.407>	<0.001>	<0.169>
In kind grant	0.021	330.575	3252.702***	247.250***
	(0.033)	(214.354)	(338.336)	(85.915)
	<0.407>	<0.129>	<0.001>	<0.011>
Cash grant	0.026	101.575	2668.871***	150.977**
	(0.032)	(190.253)	(271.595)	(63.845)
	<0.368>	<0.407>	<0.001>	<0.028>
Mean	0.378	1370.241	1838.708	153.164
Joint significance of treatments	0.000	0.494	0.000	0.010
Same effect across treatments	0.000	0.537	0.012	0.102
N	1835	1835	1835	1834
Panel B: Male Participants				
Micro credit	0.164***	-928.440***	1160.151**	145.673
	(0.036)	(351.545)	(500.140)	(248.617)
	<0.001>	<0.017>	<0.029>	<0.407>
In kind grant	0.037	-59.762	2386.322***	157.373
	(0.042)	(441.790)	(569.880)	(282.742)
	<0.346>	<0.592>	<0.001>	<0.407>
Cash grant	-0.019	-771.004*	1573.926***	344.204
	(0.042)	(400.313)	(600.716)	(386.943)
	<0.407>	<0.063>	<0.017>	<0.346>
Mean	0.440	3037.787	4237.623	935.000
Joint significance of treatments	0.000	0.018	0.000	0.819
Same effect across treatments	0.000	0.075	0.061	0.868
N	1240	1240	1240	1230
p-value: $\beta_{female} = \beta_{male}$	0.538	0.040	0.083	0.835

Notes: Column 1 is a binary variable that is equal to 1 if the individual took any loan from a bank, an MFI, family member or through ROSCA (other than the experiment loan). Column 2 is the total of loans taken from a bank, an MFI, family member or through ROSCA in addition to the experiment loan. Amounts are winsorized at the 99th percentile. The "Joint" row reports the p-value for the test for joint significance of the three treatment coefficients. The "Same" row reports the p-value for testing the hypotheses that there is no difference in the treatment coefficients. The final row reports the p-value from a test of equality of treatment coefficients by gender. Heteroskedasticity-robust standard errors in parentheses. Regressions include cohort fixed effects. Sharpened q-values that adjust for multiple hypothesis testing in angle brackets. Significance * .10; ** .05; *** .01.

Table E2: Impacts on Business Outcomes

	Has Business (1)	New Asset (2)	Monthly Revenue (3)	Monthly Expenditure (4)	Monthly Profit (5)
Panel A: Female Participants					
Micro credit	0.14***	362.52***	205.10***	152.67**	63.01***
	(0.024)	(106.210)	(77.271)	(63.759)	(19.042)
	<0.001>	<0.001>	<0.007>	<0.014>	<0.002>
In kind grant	0.24***	514.78***	490.51***	374.26***	133.24***
	(0.028)	(141.346)	(114.415)	(88.787)	(28.547)
	<0.001>	<0.001>	<0.001>	<0.001>	<0.001>
Cash grant	0.22***	470.71***	272.61***	202.57***	60.11***
	(0.028)	(142.833)	(79.047)	(66.725)	(16.314)
	<0.001>	<0.002>	<0.001>	<0.003>	<0.001>
Mean	0.15	232.25	248.16	204.34	58.86
Joint significance of treatments	0.00	0.00	0.00	0.00	0.00
Same effect across treatments	0.00	0.61	0.06	0.06	0.04
N	1835	1835	1834	1833	1834
Panel B: Male Participants					
Micro credit	0.14***	1832.62*	1101.99	707.91	135.69
	(0.034)	(1084.290)	(708.533)	(633.822)	(102.971)
	<0.001>	<0.059>	<0.076>	<0.147>	<0.116>
In kind grant	0.16***	-493.89	-117.74	-136.11	94.76
	(0.038)	(914.807)	(523.582)	(475.835)	(111.353)
	<0.001>	<0.273>	<0.363>	<0.362>	<0.207>
Cash grant	0.12***	1560.66	163.05	-292.73	63.63
	(0.038)	(1365.539)	(550.227)	(476.543)	(102.075)
	<0.002>	<0.147>	<0.362>	<0.254>	<0.254>
Mean	0.27	3325.96	2234.18	1861.99	511.07
Joint significance of treatments	0.00	0.08	0.37	0.42	0.59
Same effect across treatments	0.73	0.04	0.23	0.25	0.80
N	1240	1240	1237	1230	1236
p-value: $\beta_{female} = \beta_{male}$	0.070	0.082	0.131	0.166	0.634

Notes: Column 2 are assets bought during the year after randomization. Assets include business premises, land, equipment, and vehicles. Columns 3-5 are reported at the monthly level. Amounts are winsorized at the 99th percer "Joint" row reports the p-value for the test for joint significance of the three treatment coefficients. The "Same" row re p-value for testing the hypotheses that there is no difference in the treatment coefficients. The final row reports the p-va test of equality of treatment coefficients by gender. Heteroskedasticity-robust standard errors in parentheses. Regressio cohort fixed effects. Sharpened q-values that adjust for multiple hypothesis testing in angle brackets. Significance * .10; * .01.

Table E3: Impacts on Employment and Monthly Income

	Has Work (1)	Self Employment (2)	Wage Employment (3)	Labor Income (4)	Total Income (5)
Panel A: Female Participants					
Micro credit	0.142***	63.010***	30.561*	93.711***	86.858**
	(0.027)	(19.042)	(17.959)	(25.836)	(35.730)
	<0.001>	<0.002>	<0.121>	<0.001>	<0.025>
In kind grant	0.205***	133.237***	-14.632	118.466***	171.345***
	(0.031)	(28.547)	(15.790)	(33.060)	(46.329)
	<0.001>	<0.001>	<0.460>	<0.001>	<0.001>
Cash grant	0.214***	60.115***	58.665**	119.070***	103.726***
	(0.030)	(16.314)	(24.525)	(29.320)	(38.236)
	<0.001>	<0.026>	<0.001>	<0.001>	<0.013>
Mean	0.241	58.856	67.647	126.592	302.679
Joint significance of treatments	0.000	0.000	0.006	0.000	0.001
Same effect across treatments	0.044	0.037	0.003	0.689	0.222
N	1835	1834	1835	1834	1834
Panel B: Male Participants					
Micro credit	-0.006	135.687	-103.223	53.123	70.133
	(0.022)	(102.971)	(76.493)	(106.889)	(106.362)
	<0.697>	<0.236>	<0.236>	<0.566>	<0.543>
In kind grant	0.019	94.760	-46.684	46.791	45.248
	(0.025)	(111.353)	(89.697)	(120.944)	(120.458)
	<0.543>	<0.499>	<0.566>	<0.615>	<0.615>
Cash grant	-0.000	63.632	-85.438	-20.709	-12.710
	(0.025)	(102.075)	(90.166)	(114.267)	(113.443)
	<0.855>	<0.543>	<0.460>	<0.749>	<0.785>
Mean	0.896	511.066	1140.150	1652.855	1661.325
Joint significance of treatments	0.787	0.593	0.568	0.911	0.880
Same effect across treatments	0.595	0.799	0.824	0.808	0.785
N	1240	1236	1239	1235	1235
p-value: $\beta_{female} = \beta_{male}$	0.000	0.634	0.194	0.732	0.628

Notes: Column 2 reports income from self-employment and is the same as the "profits" column in Table 4. Column 4 is the total of columns 2 and 3. Column 5 is the total of columns 2, 3 and family and government transfers, but does not include the transfers from the experiment. Amounts are winsorized at the 99th percentile. The "Joint" row reports the p-value for the test for joint significance of the three treatment coefficients. The "Same" row reports the p-value for testing the hypotheses that there is no difference in the treatment coefficients. The final row reports the p-value from a test of equality of treatment coefficients by gender. Heteroskedasticity-robust standard errors in parentheses. Regressions include cohort fixed effects. Sharpened q-values that adjust for multiple hypothesis testing in angle brackets. Significance * .10; ** .05; *** .01.

Table E4: Time Use

	Hours Spent on:				
	Employment	Self-Employment	Home Agri.	Household Chores	Econ Tim -Use Inde
	(1)	(2)	(3)	(4)	(5)
Panel A: Female Participants					
Micro credit	0.947	5.012***	0.165	-5.543*	0.243***
	(0.705)	(1.166)	(0.439)	(2.835)	(0.062)
	<0.112>	<0.001>	<0.235>	<0.065>	<0.001>
In kind grant	0.110	8.606***	0.327	-7.591**	0.342***
	(0.843)	(1.419)	(0.564)	(3.300)	(0.076)
	<0.286>	<0.001>	<0.192>	<0.039>	<0.001>
Cash grant	1.481*	7.797***	0.089	-5.862*	0.365***
	(0.843)	(1.348)	(0.501)	(3.078)	(0.073)
	<0.007>	<0.001>	<0.286>	<0.065>	<0.001>
Mean	3.381	5.615	2.969	56.427	0.000
Joint significance of treatments	0.237	0.000	0.948	0.070	0.000
Same effect across treatments	0.363	0.039	0.919	0.817	0.204
N	1835	1835	1366	1366	1835
Panel B: Male Participants					
Micro credit	-5.269***	6.085***	0.903**	0.056	0.161*
	(1.976)	(2.028)	(0.429)	(0.942)	(0.088)
	<0.023>	<0.010>	<0.055>	<0.286>	<0.065>
In kind grant	-4.184*	5.745***	1.168*	2.441*	0.225*
	(2.250)	(2.184)	(0.633)	(1.383)	(0.116)
	<0.065>	<0.023>	<0.065>	<0.070>	<0.065>
Cash grant	-5.400**	5.730**	1.133*	0.087	0.179
	(2.258)	(2.305)	(0.614)	(1.091)	(0.116)
	<0.034>	<0.030>	<0.065>	<0.286>	<0.101>
Mean	33.773	13.962	1.147	5.452	-0.000
Joint significance of treatments	0.027	0.007	0.047	0.272	0.101
Same effect across treatments	0.861	0.984	0.890	0.153	0.876
N	1240	1240	892	894	1240
p-value: $\beta_{female} = \beta_{male}$	0.007	0.326	0.431	0.032	0.544

Notes: This table reports weekly hours spent on each activity. Column 4 includes hours spent in the household on cleani maintenance, gathering water or fuel and on childcare. Column 6 is an index of columns 1,2,3. Hours are winsorized at 99th percentile. The "Joint" row reports the p-value for the test for joint significance of the three treatment coefficients. T "Same" row reports the p-value for testing the hypotheses that there is no difference in the treatment coefficients. The fi row reports the p-value from a test of equality of treatment coefficients by gender. Heteroskedasticity-robust standard err in parentheses. Regressions include cohort fixed effects. Sharpened q-values that adjust for multiple hypothesis testing angle brackets. Significance * .10; ** .05; *** .01.

Appendix F:
Description of Machine Learning Methods

In this appendix we describe in more detail the machine learning methods we utilize in section 4. We follow the method put forth in Chernozhukov et al. (2020). The intuition behind the method is that machine learning is really good at generating highly predictive models. The method generates models for the predicted outcome (in our case total income) using only baseline data. It produces one model for those in the control group and a separate model for those in the treatment group. The difference between these two predictions is the estimated individual treatment effect. It then groups people based on their predicted individual treatment effect, and estimates an interacted model for how the treatment effect differs for people in each group.

Critically it uses split sample validation and conservative inference procedures to ensure that these estimates are "honest". It does this by first randomly spliting the sample into a "training set" and a "testing set". It generates the models using data from the training set and then uses those models to predict for each person in the testing set what their income would have been if they were in the treatment group or in the control group. It then implements this procedure 100 times, each time randomly changing composition of the training testing sets, and then takes the median coefficients from the associated regressions.

In a bit more detail, to estimate heterogeneity in the treatment effect for income, first, using the training set only, we train a machine learning (ML) method to generate a "control" effect $B(Z_i)$ (i.e. the expected outcome for those with covariates Z if they were assigned to control) and predicted treatment effect $S(Z_i)$, where Z_i denotes the full set of covariates used to predict heterogeneity for subject i (in this case all of our relevant baseline data). Any machine learning methods could be used, but we use the four options included in the original code in Chernozhukov et al. (2020) (elastic net, neural net, random forest, and gradient boosting) and then take the one with the highest prediction score. This is defined as $|\hat{\beta}_2|^2\widehat{Var}(S(Z))$ where β_2 is defined in equation (E1) below. Note that because we utilize all four ML methods and choose the one with the highest prediction score we utilize a conservative Bonferroni correction in our estimates and multiply all of the p-values by 4, in line with Chernozhukov et al. (2020). In all cases we use the implementation of these methods from the R package caret.

With the estimates $B(Z_i)$ and $S(Z_i)$ in hand we then undertake two analyses using only data from the testing set. First, we estimate the regression

$$Y_i = \alpha * X_i + \beta_1 * T_i + \beta_2 * T_i * S(Z_i) + \epsilon_i \tag{E1}$$

where X_i is a set of covariates that includes $B(Z_i)$ and T_i is an indicator for treatment group.[28] Our primary use for this specification is to test the null hypothesis of no heterogeneity $\beta_2 = 0$.[29] Second, we split the testing sample into quintiles of predicted treatment effect using $S(Z_i)$ and estimate the regression

$$Y_i = \alpha * X_i + \sum_{j=1}^{5} \gamma_j * T_i * 1(S_i \in I_j) + \eta_i \tag{E2}$$

where I_j is the set of firms in the jth quintile.[30] γ_j measures the "sorted group average treatment effect" (GATES) for each quintile, and is the key measure that we use to understand how treatment effects differ across well defined groups.

The key contribution of Chernozhukov et al. (2020) is to show how to get theoretically correct inference for these analyses and, again, we follow their approach. We repeat the split into training and testing sets 100 times (each with a different randomly chosen split) and run the analyses in (E1) and (E2) for each split. This process produces estimates of the key parameters β_2 and γ_j for each of the 100 splits, as well as the associated confidence intervals, standard errors and p-values. For the parameter estimates we report the median from the 100 runs. For a $1 - \alpha$ confidence interval we report the median of each boundary of a $1 - \alpha/2$ confidence interval from each split. For hypothesis tests in equation (1), we state that a hypothesis is significant at the α level if the median p-value is less than $\alpha/2$. The use of $\alpha/2$ in the hypothesis tests and confidence intervals corrects for sample splitting. As mentioned above, due to the initial test of 4 machine learning prediction methods we implement a Bonferroni correction by multiplying p-values by four.

[28] The treatment assignment is included as the treatment binary minus a propensity score associated with treatment assignment. The propensity score is constant due to the randomized treatment assignment. The individual treatment effect $S(Z_i)$ is included as a deviation from its mean.

[29] $\beta_2 = 0$ if there is no heterogeneity, or the ML prediction $S(Z_i)$ does not capture that heterogeneity. Hence, this test is of a joint hypothesis, that there is heterogeneity and that the ML methods can detect it using the covariates that we have.

[30] Again, the treatment assignment is included as the treatment binary minus a propensity score associated with treatment assignment.