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Does microcredit increase aspirational hope? Evidence from a group lending scheme in Sierra Leone

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Does microcredit increase aspirational hope? Evidence from a group lending scheme in Sierra Leone*

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Abstract

Microcredit has received considerable attention because of its potential to help achieve the Sustainable Development Goals (SDGs), in particular through poverty alleviation, female empowerment and self-employment. To date, its effectiveness has largely been evaluated in terms of relieving *external* constraints of the poor, such as a lack of financial capital for business development. The current study examines whether, and to what extent, microcredit can affect *internal* constraints, such as aspirational hope. We use a cross-sectional dataset of 1295 women in Sierra Leone, 854 of whom are active borrowers of a Microfinance Institution, BRAC. To estimate the impact of microcredit on aspirational hope and economic welfare we rely on BRAC's eligibility criteria, that only allow access to finance for women living with-in 4km of a BRAC branch. We find statistically significant and economically meaningful positive impacts on both aspirational hope and economic welfare. Overall, this study suggests that microcredit plays an important role in reducing internal psychological constraints, and via this channel contributes to the realization of the SDGs.

Keywords: Microcredit; Aspirational hope; Well-being; Poverty; Sierra Leone

JEL Codes: C83, G21, I31, O12, Z13

Highlights

- Microcredit has the potential to help achieve the Sustainable Development Goals (SDGs)
- In contrast to earlier work, which focusses on external constraints, we look at internal constraints such as aspirational hope
- We rely on MFI eligibility criteria and find that microcredit increases both aspirational hope and economic welfare.
- A possible channel linking microcredit to aspirations are through increased social connectedness and exposure to role models in lending groups

Introduction

Microcredit programs provide small loans to poor entrepreneurs to help them start, or expand, their own businesses. Since its origin in Bangladesh in the 1970s, microcredit has rapidly expanded to other developing countries and has received substantial attention due to its promising potential to help achieve the Sustainable Development Goals (SDGs), in particular through poverty alleviation, female empowerment and self-employment. But even as microcredit has grown in scale and scope, debates about its effectiveness continue among policy makers, nongovernmental organizations, and academics (Morduch, 2000, Hermes & Lensink, 2011, Banerjee, 2013). Proponents emphasize that microcredit helps poor people invest in productive activities, which eventually leads to increased income, consumption smoothing, and improvements in health, education, and women's empowerment (Hermes & Lensink, 2011). However, critics question whether microcredit can fulfill its promises since, e.g. due to commercialization, several microfinance institutions (MFIs) experience mission drift. The mission drift implies that they might focus on better-off urban clients, shifting away from poor female borrowers in rural areas. Moreover, some MFIs have started lending at high interest rates (Mersland & Strøm, 2010). In addition, a set of recent microcredit impact studies conclude that, while microcredit positively impact the poor, the effect sizes are small and non-transformative (Banerjee, Karlan, & Zinman, 2015). Yet, as it has been argued by Duvendack (2019), among others, more studies are needed to obtain a definitive answer regarding the impact of microcredit.

We evaluate the impact of BRAC's microcredit program in Sierra Leone, which operates according to a group lending scheme with joint liability. While most prior microcredit studies assume that potential positive impacts will materialize by means of reducing credit constraints, i.e. by relieving *external* constraints, our study takes another route. We argue, in line with a set of recent studies (Beaman et al , 2012; Bernard et al 2014; Lybbert & Wydick, 2017; Macours

& Vakis, 2014, 2017) that in order for interventions to be transformative, they require that internal constraints, such as agency, hope and aspirations, are addressed. Duflo (2012) argues that hope is fundamental for development; low aspirations and hopelessness lead to reduced investments and outcomes that ultimately reduce long-run welfare. In this study, we provide evidence that access to microcredit increases both material well-being and releases *internal* psychological constraints (aspirational hope). As such, our study provides evidence for a new, and so far ignored, channel by which microcredit may improve welfare and contributes to realizing the SDGs.

In our theory of change, we argue that changing external constraints (like access to credit) will only affect outcomes if internal constraints are not binding, i.e. if aspirations are not too low. We hypothesize that BRAC's microcredit scheme with joint liability is associated with an increase in aspirations, such that the internal constraint will not bind anymore and as a result credit increases welfare. This in turn may further improve aspirational hope of borrowers, igniting a dynamic upward process.

We use a unique, self-collected, cross-sectional data set involving 1295 women in Sierra Leone, 854 of whom are borrowers of BRAC Sierra Leone. Only women living within a radius of four kilometers (km) from the branch office are allowed to borrow. By sampling eligible women within and outside this radius from the BRAC branch office, we are able to reduce selection biases in our estimates. As our empirical strategy, we use a matching approach with inverse probability of treatment weights (IPTW) and a cross sectional difference-in-difference (DID) approach. Our preferred model relies on the DD approach as it also partly controls for selection biases due to unobservables.

Using the DD estimates, we find that microcredit participation is positively related to aspirational hope and economic welfare. We also present suggestive evidence, in line with our theory of change, that an increase in aspirational hope acts a mediator for the effects of

microcredit on welfare. In addition, we show that aspirations correlate with both social interaction and role models, which are potential channels by which microcredit may enhance aspirations.

Overall, our study suggests that microcredit may play an important role in reducing internal psychological constraints, which may improve the contribution of microcredit interventions to the realization of the SDGs. We, however, also recognize that our identification approach suffers from potential selection biases, implying that our result should be interpreted as descriptive rather than inferential.

Theoretical framework

Aspirational hope

A small but emerging literature assess the role of hope and aspirations in helping understand how people can move out of poverty or remain stuck at low levels of income and food security. At its core, aspirational hope comprises three elements: aspirations, agency and pathways (Lybbert & Wydick, 2018). The concept of aspirational hope finds its roots in a conceptual framework proposed by Snyder (2002) and Appadurai (2004) . They argue that individual aspirations originate from the sense that each person is part of a larger ethos within a particular reference community. Ray (2006) builds on this notion by integrating an economic perspective, such that he defines aspirations as "social grounding of individual desires" which are largely determined by own experience and observing others.

In addressing the effect of aspirations on individual behavior, Ray (2006) introduces three aspiration concepts: the aspirations window, aspirations gap, and aspirations failure. An aspirations window is formed by observing similar individuals. The aspirations gap instead refers to the difference between the life that people aspire (i.e. aspiration window) and their current life. This gap affects future-oriented behavior. To close it, individuals must make

investments that they expect to enhance their lives. This investment is costly though. Accordingly, for people to improve their lives, the aspiration window must be opened, but not too wide or too narrowly to avoid discouraging forward-looking behavior. When the aspirations gap is too wide or narrow, it might become an aspiration failure.[1]

Ray (2006) further suggests that the capacity to aspire, and forward-looking behavior, depends on collective action. First, groups have information and experiences that can be communicated credibly to members. Second, group actions convey information to external parties more credibly than do individual actions. Third, groups function as coordination devices. Thus, group effectiveness can be explained in terms of a multiple equilibrium: "*A state x persists in society, which leads individuals in the society to take actions a. The actions a aggregate back to x, and the cycle is complete*" (Ray, 2006, p. 9).

An empirical study in rural Nepal, by Janzen et al. (2017) provides supportive evidence for these theories. They show that aspirations indeed might be socially formed due to correlations between aspirations and outcomes (e.g. income and education) of other individuals in her higher-status network. They also find that an aspirations gap encourages forward-looking behavior by increasing investment, but when the gap is too large investment decreases.

Lybbert and Wydick (2018) introduce a theoretical model that formally defines the three elements of aspirational hope in an economic context. It shows how these elements can contribute to improved development outcomes and their relationship with economic and psychological interventions. In the model, an individual maximizes utility from an outcome conditional to her aspirations, subject to external constraints emerging from the structure of

[1] Dalton, Ghosal, and Mani (2016) present a theoretical framework showing that poverty can lead to aspirations failure and eventually to a behavioral poverty trap. They stress that aspirations failure is a result of poverty and not the opposite and that, under certain conditions, increasing aspirations alone might be enough to avoid poverty traps, even when external constraints do not change. However, poverty is not the only source of aspiration failure; it is the combination of poverty and a lack of connectedness—that is, a lack of proximal others who are better off than the focal person, but not so much better off that they seem unreachable.

production. Aspirations are considered to be socially determined and not endogenous to the model, but they can be influenced by exogenous interventions.

One of the main implications of the aspirational hope model is that a standard economic intervention which focuses on relaxing external constraints (schooling, health, credit, agricultural productivity) will not change effort, and hence outcomes, if internal constraints are binding, for example when aspirations are low. However, if internal constraints are not binding, an intervention that changes external constraints, will increase outcomes. Similarly, an intervention that increases aspirations, will generate an aspirations gap, which may encourage individuals to take actions to narrow it. Improved agency as productivity of effort increases the generated outcomes.

Interventions that enhance aspirational hope

Several recent development interventions have aimed to enhance aspirations. Most of these interventions focus on improving aspirations by either exposing individuals to role models (Beaman et al., 2012; Bernard et al., 2014; Lybbert & Wydick, 2017; Macours & Vakis, 2014; Riley, 2017), or by stimulating interactions with peers (Dasgupta, Scircle, & Hunsinger, 2015; Field, Jayachandran, Pande, & Rigol, 2016).[2]

For reasons of space, we cannot elaborate on all studies in detail. Two studies are worth discussing here. Lybbert and Wydick (2017) conduct a field experiment in Mexico, which explicitly aimed at enhancing aspirations, agency, and pathways. Their intervention among female members of community banks consists of three elements: (1) watching a documentary

[2] While most interventions to enhance aspirations use role models and/or peer effects, there are some exceptions. For instance, Chiapa, Garrido, and Prina (2012) provide evidence from Mexico showing that an antipoverty program increases the educational aspirations that parents have for their children. There are also examples of interventions that failed to improve aspirations. An example is Baranov, Haushofer, and Jang (2019), who find no effect on aspirations among people who received a light-touch low-cost psychological intervention in Kenya, designed to promote aspirations, gratitude, self-affirmation.

about women successfully using microcredit to expand their businesses, (2) receiving a refrigerator magnet on which they write three personal goals, and (3) participating in a workshop designed to help them lift aspirations, set goals, improve agency, and visualize pathways. After one month, the researchers identify positive impacts on aspirations and modest impacts on agency and business outcomes among women who received the three-component intervention. In Nicaragua, Macours and Vakis's (2014) randomized evaluation focuses on cash transfer programs that aim to improve human capital and productive investments. Their study indicates that social interactions with leaders improve agency and aspirations through role-modeling, inspiration, and learning effects, which prompt greater investments in children's nutrition and education. The closer the participants live to the leaders, the stronger these effects.

Microcredit and aspirational hope: theory of change and hypothesis

Based on the theories and empirical evidence outlined above, we argue that microcredit provided via a group lending scheme improves social interactions and induces exposure to role models during the weekly meetings, which potentially enhances aspirations. Our first hypothesis hence is:

Hypothesis 1*: Participation in a microcredit group lending scheme enhances aspirations.*

We also argue that microcredit potentially improves agency by improving the productivity of individual efforts and opens pathways by relaxing credit constraints. It might shorten the steps to success, for instance by providing financial capital to start a new business, which implies that goals are within reach. This may encourage individuals to take necessary actions to reach their goals. The second hypothesis that we will test will therefore is:

Hypothesis 2: *Participation in a microcredit group lending scheme enhances agency and pathways.*

The model of Lybbert and Wydick (2018) implies that microcredit will only increase economic welfare if aspirations are not too low, and that individuals will put in more effort to improve production if participation in a microcredit program enhances aspirations. Consequently, participation in a microcredit program will probably (at the least partially) affect economic outcomes via an increase in aspirations. Our third hypothesis therefore is:

Hypothesis 3: *Participation in a microcredit group lending scheme enhances economic outcomes partly through aspirations.*

Figure 1, below, provides a schematic explanation of our theory of change (TOC). Our TOC hypothesizes that participation in a microcredit group lending scheme enhances aspirational hope. It also shows that the participation in a microcredit group improves economic welfare, if aspirations increase or if aspirations are high enough such that they are not binding. That is, microcredit party affects economic welfare via aspirations, but there may also be a direct effect from microcredit to economic welfare.

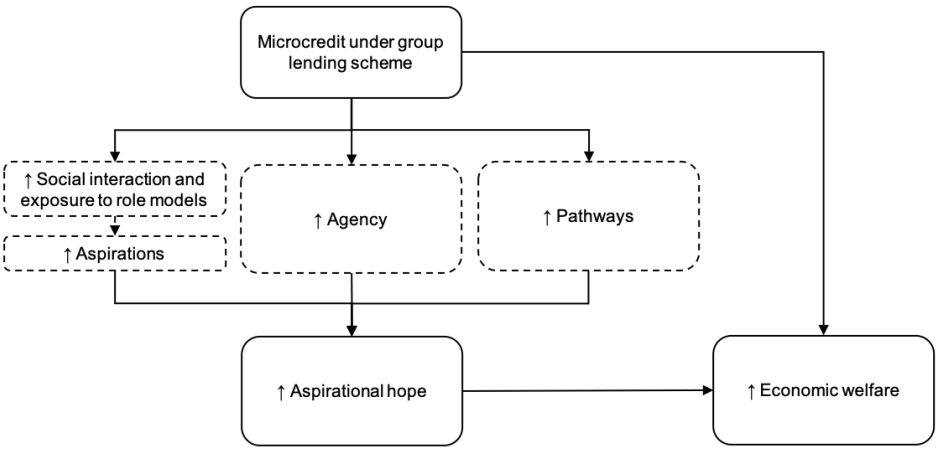

Figure 1. Theory of Change for Microcredit

Microcredit program and study setting

Sierra Leone, still recovering from a 11-year civil war that ended in 2002, is a low-income country; half of the population lives on less than US$1.90 per day (The World Bank Group, 2017b). The financial sector in the country is extremely underdeveloped, such that among the economically active population, only 13% have access to financial services (idem). For the women in our sample, the main sources of credit, beyond BRAC, are relatives, friends, neighbors, and *osusus*—a rotating savings and credit scheme.

BRAC, one of the largest MFIs in the world, aims to alleviate poverty by empowering the poor. It functions in 11 countries in Asia and Africa, including in Sierra Leone since 2008. They provide loans to women using a group lending methodology with joint liability, to help expand their own business, mainly small-scale trading. Loans are provided to woman individually, but each recipient is accountable for repayment by her group members also. In 2014, BRAC Sierra Leone disbursed US$2.8 million in loans, with an average loan of US$145. It served about 22 thousand women through its 29 branch offices across the country (BRAC, 2014).

When BRAC opens a new branch office, loan officers conduct door-to-door visits strictly within a 4-km radius to find potential borrowers and introduce them the microcredit program. In addition, potential borrowers must meet the following criteria: female, aged 18–50 years, own a business, no outstanding loans with other MFIs, has lived in the area for at least three years, and limiting to one member per household. The loan officer returns for a second visit to ask eligible women if they are interested in joining the program. Those interested form small groups of four to five women and apply for individual loans with a joint liability scheme. Finally, the loan officer decides whether the groups may enter the program.

The accepted small groups then meet every week, clustered in bigger groups. Each small group has a president; each big group includes a leadership committee of five women:

president, secretary, treasurer, and two executive members. Every two weeks, two group members receive a loan, the size of which varies among members. The interest rate is 13% if the loan is for 20 weeks and 25% if the loan is for 40 weeks. The loan gets repaid weekly, during group meetings. The president of each small group collects repayments and transfers them to the treasurer of the big group, who then gives them to the loan officer. If someone is not able to make a payment, the group members pay for her. However, if this failure occurs repeatedly, the member may be expelled, and another eligible woman will be invited to join the group.

Sampling strategy and data

We use data from a survey implemented in Sierra Leone in 2014, after the BRAC microcredit program had already started. The survey collected data in seven small towns with a BRAC branch office, randomly selected from among 29 locations throughout Sierra Leone where BRAC operates. We stratified our sample to include women both within the catchment area of 4 km around the branch office and just within 4-8km. In total, we surveyed 1295 women, of which 1086 lived within the 4km radius regardless of whether they decided to participate and became borrowers or not, and 227 non-borrowers who lived too far from the branch office to be allowed to borrow.

By leveraging these eligibility rules, we established a clear sampling strategy that ensured we surveyed women with similar characteristics. Table 1 summarizes our sample: of the 1068 women eligible for the program, 854 were active borrowers and 214 were not.

Table 1 – Sample

	Access area (Inside 4 km radius from BRAC branch office)	Non-access area (4–8 km radius from BRAC branch office)	Total
Eligible participants	854		854
Eligible nonparticipants	214		214
Not eligible		227	227
Total	1086	227	1295

We distinguish two families of outcome variables: aspirational hope and economic welfare. We discuss each in turn below. Table 2 summarizes the descriptive statistics.

Aspirational hope. We use four types of indicators to capture aspirational hope: agency and pathways, life aspirations, aspirations gap and perceptions of future economic welfare. The first two measure the core elements of aspirational hope separately and the other two measure aspirational hope as a whole.

We create an *agency and pathways index* using six statements of the Trait Hope Scale developed by Snyder et al. (1991), four of which capture agency and two pathways (see also Bloem, Boughton, Htoo, and Hein (2018) who validate this scale in rural Myanmar to show that it indeed measures these elements of hope and not other concepts). However, we note that this index is subjective and broad. It unfortunately does not capture opportunities that the microcredit program opens itself in terms of relaxing external constraints. Thus, the index may not pick up the entire scope of pathways and agencies that can be enhanced by participation in a microcredit program. We presented respondents with six statements and asked them to indicate if they strongly agree = 1, agree = 2, disagree = 3 or strongly disagree = 4 with each statement. We inverted the scale of the answers such that the higher values indicated stronger agreement with the statement. We then use principal component analysis (PCA) to create the index.[3]

To construct the *life aspirations* variable, we presented the women with an image of a cotton tree, the historic symbol of Sierra Leone, divided into ten levels, such that the tenth level is the best possible life and the lowest level is the worst. We asked them to indicate the level they aspire to. On average, respondents aspired to reach the ninth level.

[3] The internal correlation between the measures is high, Cronbach's alpha = 0.86. Kaiser-Meyer-Olkin (KMO) test of sampling adequacy for our index is 0.86 - 0.87.

We also capture respondent *aspirations gap*, measured as the difference between their desired level and current level. The average aspirations gap is 4.72; that is, women want their lives to be almost 5 levels higher than they actually perceive them to be.

In addition, we use two measures that reflect *perceptions of future economic welfare*. We asked two questions: "what would your income per month be in the coming year if it were a good year?" and "what would your income per month be in the coming year if it were a bad year?". These questions are arguably related to aspirational hope because: visualizing higher monthly income in the next year might imply that a woman has the aspiration of a better economic situation, has the self-determination to achieve the goal (e.g. by expanding a business), and sees a pathway to achieve it (e.g. the microcredit program). On average, women consider that their monthly income if the coming year were a good year would be US$304 and US$129 if it were a bad year, equivalent to US$1.45 and US$0.61 per day per household member, respectively.

Economic welfare. We ask about household income in the current month[4]. On average, monthly income was US$220. Expressed as daily income per household member, this amounts to US$1.05, just below the poverty line. We also created an index for household durable assets. It is constructed as the sum of 19 dummy variables that indicate whether the household owned durable assets, such as a bed, motorbike, television, phone, refrigerator, and sewing machine. The average respondent owns 9 assets.

For our analysis, we standardized life aspirations, agency and pathways index, life aspirations gap, and household durable assets index to have a mean of zero and a standard deviation of one. We transformed monthly income in good and bad year and monthly income of current year are presented to their logarithmic form.

[4] We winsorized the income proxy at 5% and 95% and used logarithmic transformations.

In addition to the outcome variables, we gathered information about socio-economic characteristics.

Socio-economic characteristics. On average, the women in our sample were 34 years of age, 77% are Muslim, and 60% belong to the Temne tribe, the largest ethnic group in Sierra Leone. Their households consist of an average of seven members, three adults and four children. On average, 33% of the households had outstanding loans. We find significant differences based on location: on average, within the 4-km radius, women are 2 years older, their households are larger, and more of them practice Islam (16%) and belong to the Temne tribe (21%). As would be expected, 39% of households in the "access" region have outstanding loans (from all types of financial intermediaries), while this only holds for 9% of households in the non-access area, which clearly suggests that access to microcredit enhances borrowing possibilities.

Table 2 – Summary Statistics

	Total sample			Access area			Non-access area			Access vs Non-access
Variables	N	Mean	SD	N	Mean	SD	N	Mean	SD	
Aspirational Hope										
Agency and pathways index	1,215	0	1.896	1,005	-0.047	1.873	210	0.223	1.992	-0.270*
Life aspirations	1,219	9.343	1.513	1,008	9.376	1.469	211	9.185	1.704	0.191
Aspirations gap	1,219	4.270	1.876	1,008	4.274	1.929	211	4.251	1.600	0.0226
Monthly income in good year (US$)	1,171	303.8	267.3	958	307.6	276.4	213	286.6	221.6	21.38
Monthly income in good year (log)	1,171	12.90	0.986	958	12.90	0.997	213	12.90	0.937	-0.004
Monthly income in bad year (US$)	1,169	128.5	119.0	956	131.9	122.6	213	113.4	99.95	18.45**
Monthly income in bad year (log)	1,169	11.98	1.035	956	12.00	1.045	213	11.90	0.987	0.094
Economic welfare										
Income current month (US$)	1,157	220.0	203.1	953	224.9	209.0	204	197.3	171.5	27.65**
Income current month (log)	1,157	12.51	1.060	953	12.52	1.074	204	12.46	0.990	0.061
Household durable assets index	1,200	9.047	2.577	983	9.048	2.648	217	9.041	2.230	0.0063
Socio-economic characteristics										

Age	1,279	33.80	8.634	1,052	34.13	8.725	227	32.27	8.040	1.861***
Temne (tribe)	1,271	0.601	0.490	1,049	0.638	0.481	222	0.428	0.496	0.210***
Muslim (religion)	1,268	0.771	0.420	1,048	0.799	0.401	220	0.641	0.481	0.158***
Number of adults in household	1,276	3.512	1.889	1,050	3.563	1.909	226	3.274	1.775	0.289**
Number of children in household	1,271	3.873	2.401	1,046	3.987	2.450	225	3.347	2.082	0.640***
Households with outstanding loans	1,267	.3346	.4720	1,040	.3884	.4876	227	.0881	.2841	.0300***

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Exchange rate: 1 US$ = 1976 Sierra Leone PPP 2014 (The World Bank Group, 2017a). N: Number of observations. SD: Standard Deviations.

Methodology

One of the main challenges associated with measuring the impacts of microfinance is controlling for selection bias, which stems from two sources: self-selection bias and program placement bias. Self-selection may bias the results if people self-select to participate in a program due to unobserved characteristics; for example, the most innovative or entrepreneurial women might be the ones who decide to take up microcredit. Program placement biases may result from institutional decisions regarding strategic locations; BRAC often seeks to open branch offices in the most underdeveloped regions, to reach the poorest of the poor. These biases can be addressed using randomization, such that we would randomly assign the program to individual participants and randomly assign locations of branches. However, random assignment is not always possible; in our case, the BRAC microcredit program had started before we began to evaluate it. Therefore, we rely on quasi-experimental methods to control for selection bias, we discuss different strategies below, relying on matching and a double difference estimator.

Identification strategies

Microcredit access. The most straightforward method to control for self-selection into the program is an intention to treat (ITT) analysis. In its most simple form, it estimates the impacts of having access to microcredit by comparing access and non-access areas, which we can define

clearly using the distance to the branch office as an eligibility rule. This approach would provide unbiased estimates of the impact of access to credit if both areas are similar—that is, if there is no program placement bias. However, this assumption likely does not hold for our study, because BRAC offices are strategically located. Consequently, as can be seen in Table 2, access and non-access areas differ in terms of the women's characteristics. Women in access areas are older, more likely to be Temne and Muslim, have larger households and are more likely to already have loans (from any source).

To partly address such selection bias, we use inverse probability of treatment weighting (IPTW) and make use of the fact that access to microcredit (*A*), is determined by a four km radius from a BRAC branch. Using these weights, we obtain balanced (weighted) variables for access and non-access areas.[5] We then estimate the impacts of microcredit access on each outcome *Y* for woman *i* in area *j* by weighted least squares (WLS), with the following equation[6]:

$$Y_i = \alpha_0 + \alpha_1 A_j + \varepsilon_i \quad (1)$$

Microcredit participation. Because we are primarily interested in the impacts of microcredit on women who actually participated in the program, we use two alternative methods. This measurement effort is more challenging, in that it entails both self-selection and program placement biases.

Participation 1: inverse probability of treatment weighting (IPTW). As a first strategy to estimate the impacts of microcredit participation, we control for selection biases using observed characteristics. We again apply IPTW, but in this case, the treatment is uptake of microcredit (*U*). Using equation (1) – but replacing *A* (access) with *U* (uptake) – we estimate

[5] Refer to Appendix 1 for details on the procedure to estimate stabilized weights.
[6] Note that the weighting implies that original variables are redefined, and the model is estimated with the transformed variables.

the impacts of microcredit participation, controlling for program placement bias with observed characteristics[7].

Participation 2: cross section double difference (DD). A disadvantage of matching is that that it does not control for bias due to unobserved characteristics. We use an alternative approach relying on a double difference across space methodology (akin to Coleman 1999) allowing us to control for location specific characteristics.

For specific details on the methodology and a discussion on its limitations, see Appendix 2. The DD approach can be summarized as follows. We start by estimating the propensity to participate in the microcredit program by using data from households (participants and non-participants in the microcredit program) in the access area only. We then forecast *expected* participants and non-participants in the non-access areas by conducting an out-of-sample forecast. We also reclassify actual participants and non-participants in the access area into *predicted* participants and no-participants in the access area [8], and indicate *predicted* participants (in both the access and non-access area) with a binary dummy: $\widehat{U}$. We then specify the following cross-sectional DD model to estimate the impact of the microcredit program:

$$Y_i = \beta_0 + \beta_1 A_j + \beta_2 \widehat{U}_i + \beta_3 A_j \times \widehat{U}_i + \sum_{h=1}^{H} \gamma_h X_{ih} + \sum_{k=1}^{K} \theta_k Z_k + \mu_i, \qquad (2)$$

where Y_i is the outcome variable of woman *I*, A_j is a binary variable indicating availability of the MFI (equal to 1 within the access area, and 0 otherwise); $\widehat{U}$ is a binary variable equal to 1 if woman *i* in region j is estimated to take up microcredit (irrespective of whether an MFI is available), and 0 otherwise; $A \times \widehat{U}$ is the interaction term between these two variables, i.e. 1 for women living in the access areas who are estimated to take up a loan; the *X's* indicate household controls; Z is a vector of K district-level dummy variables and μ_i is the error term.

[7] See Appendix 1 for details on estimation.
[8] Note, we do not use actual participants and non-participants as unobserved factors may increase participation in the microcredit program as well as affect our outcome variables (i.e. aspirations).

Note that the β coefficients are easy to interpret if we ignore the control variables *X* and *Z,* which were added to improve precision of the estimates and to control for differences in measured attributes. The following then holds: the constant β_0 measures the mean of the outcome *Y* for (forecasted) nonparticipants in the non-access area, $\beta_0 + \beta_2$ equals the mean for (forecasted) participants in the non-access area, $\beta_0 + \beta_1$ indicates the mean for (forecasted) nonparticipants in the access area, and $\beta_0 + \beta_1 + \beta_2 + \beta_3$ measures the mean for (forecasted) participants in the access area. The parameter of interest is β_3; it captures differences between (forecasted) participants and nonparticipants, controlling for self-selection bias (β_2) and program placement bias (β_1).

Intuitively, the cross-sectional DD approach works as follows: the first differences are between participants and nonparticipants within each area, which controls for program placement bias, such that $(\beta_0 + \beta_1 + \beta_2 + \beta_3) - (\beta_0 + \beta_1) = \beta_2 + \beta_3$ for the access area and $(\beta_0 + \beta_2) - \beta_0 = \beta_2$ for the non-access area. The second difference is between the two areas, which eliminates self-selection bias, that is, $(\beta_2 + \beta_3) - \beta_2 = \beta_3$[9].

Basically, our methodology combines propensity score with a DID methodology. It improves identification when baseline data is not available, by revealing whether predicted microcredit participants in the access area are performing better than predicted non-participants in the access area, vis-à-vis the difference between predicted participants and non-participants in the non-access area. While we do prefer the DID approach, the methodology is not without limitations, as we explain in greater detail in Appendix 2. The methodology, for instance, assumes that the selection process is similar in the access region and the non-access region

[9] As $\widehat{U}$ is a generated regressor, which may lead to biased standard errors if we estimate the equation using OLS, we use a bootstrapping procedure to determine standard errors. Specifically, we wrote a small stata.ado program that enables us to estimate Equation 2 simultaneously with the procedures to estimate expected participants in the non-access area, as well as bootstrap the entire process. More details (and the stata.ado file) are available on request.

(which we explicitly test, see Appendix 2). Moreover, as we do not have information about who wants to take up micro-credit in the non-access area would an MFI be available, we have to rely on "estimates". Finally, our sample for the non-access area is relatively small[10].

Results

Impact of microcredit access

Table 3, Panel A presents the results of the estimates for *Access* to the microcredit program, using Equation 1 above. We find an increase in both aspirations and welfare. Specifically, life aspirations increase by 0.28 standard deviations and expectations of future earnings by 18% to 26%, depending on whether the respondent expects the subsequent year to be good or bad. In addition, actual income and assets holdings increase by a sizable amount: access to credit increased incomes by 21% and asset holdings by 0.26 standard deviations or 0.67 additional assets.

Impact of microcredit participation using Inverse probability of treatment weighting (IPWT)

Table 3, Panel B present results for participation in microcredit. The table shows positive coefficients throughout (except for aspirations gap, as expected) and points to a significant and large increase in life aspirations (0.26 SD).

Table 3. Impacts of Microcredit Access and Participation using IPTW

		Aspirational hope				***Economic welfare***	
	Agency and pathways index	Life aspirations (std)	Aspirations gap (std)	Monthly income in good year (log)	Monthly income in bad year (log)	Monthly income current month (log)	Household durable assets index (std)
Panel A: Impact of microcredit access							
Access	0.00481	0.277**	0.0433	0.183*	0.258**	0.213*	0.261***
	(0.198)	(0.134)	(0.111)	(0.105)	(0.104)	(0.115)	(0.0999)

[10] To further test the reliability of our DID approach we conduct a placebo test, see Appendix 2. This placebo test provides some additional support to our analysis.

Panel B: Impact of microcredit participation							
Uptake	0.0832	0.263**	-0.0417	0.0742	0.119	0.150	0.145
	(0.167)	(0.121)	(0.0978)	(0.0949)	(0.0972)	(0.0968)	(0.0967)
Observations	1,161	1,165	1,165	1,120	1,118	1,106	1,148

Notes: Life aspirations, life aspirations gap, and household durable assets index are standardized to a mean of zero and a standard deviation of one. Monthly income in good and bad year and monthly income of current year are presented in their logarithmic transformation. Robust standard errors are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Impact of microcredit participation using a Cross-Sectional Difference-In-Difference approach.

Table 4 below presents the results, using the DID methodology.

Aspirational hope. We find statistically significant impacts of microcredit participation on life aspirations, an increase of 0.48 standard deviations, supporting our first hypothesis. There is a positive but non-significant effect of microcredit participation on improving agency and opening pathways of women. This result is not in line with our second hypothesis, potentially as our Trait Hope Scale may not capture the entire scope of pathways and agencies that can be enhanced by participation in a microcredit program.

Although the effect is not significant, the negative coefficient suggests that microcredit participation can potentially reduce the aspirations gap. Unfortunately, our data are not rich enough to further explore the dynamics between these two variables over time or to test whether it encourages forward-looking behavior.

For aspirational hope of future economic welfare, we find significantly positive impacts of microcredit participation on expected changes in economic welfare, increasing expected income by 39% if respondents expect next year to be a good year or 28% for expected bad years (though this effect is not significant at conventional levels)

Over all, the results show indicative evidence that microcredit participation has strong effects on aspirational hope.

Economic welfare. Our evidence suggests an overall positive impact of microcredit on welfare; both coefficients are positive. Current monthly income increases by about 10%, a sizable amount, yet estimated with considerable noise. We find positive and significant effects of microcredit participation on the household durable assets index, which increase by about 0.6 SD. These findings are similar to the findings by Attanasio et al. (2015) in Morocco, who show positive and significant effects of microcredit access on the stock of household durables. However, there is no consensus in the literature about this outcome. For instance, Augsburg et al. (2015) in Bosnia and Banerjee, et al. (2015) in India find that access to microcredit reduced the stock of durable assets, though the effect in India was not significant.

The positive and significant impact on the household durable assets index supports our third hypothesis: microcredit increases economic outcomes. In the section below, we analyze whether this effect is partly generated *through* increases in aspirations.

Table 4 – Impacts of Microcredit Participation using cross-sectional DD approach

		Aspirational hope				***Economic welfare***	
	Agency and pathways index	Life aspirations (std)	Life aspiration gap (std)	Monthly income in good year (log)	Monthly income in bad year (log)	Monthly income current month (log)	Household durable assets index (std)
Uptake x Access	0.451	0.478**	-0.252	0.390**	0.277	0.109	0.604***
	(0.399)	(0.239)	(0.176)	(0.198)	(0.183)	(0.213)	(0.191)
Uptake	-0.532	-0.424*	0.0261	-0.264	-0.0236	0.317	-0.485***
	(0.439)	(0.254)	(0.177)	(0.195)	(0.203)	(0.222)	(0.187)
Access	-0.365*	-0.0438	0.129	-0.0527	0.0685	0.142	-0.177**
	(0.211)	(0.102)	(0.0879)	(0.0876)	(0.0991)	(0.102)	(0.0902)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,161	1,120	1,118	1,165	1,165	1,106	1,148

Notes: Life aspirations, life aspirations gap, and household durable assets index are standardized to a mean of zero and a standard deviation of one. Monthly income in good and bad year and monthly income of current year are presented in their logarithmic transformation. Control variables are: age, adults, children (linear and square), Temne (tribe), and Muslim (religion). Bootstrapped standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Mediation analysis

In line with our theory of change, we find effects on some measures of aspirational hope and economic welfare. We also argue that these families of outcomes may impact each other. However, our data restrict us to conduct rigorous analysis and control for all endogeneity issues. Acknowledging this, we conduct an exploratory mediation analysis by Baron & Kenny (1986) to provide descriptive rather than causal evidence. The main treat to this analysis are violations of the sequential ignorability assumption (Imai, Keele, & Yamamoto, 2010), that is, unconfoundedness in both outcomes and mediators.

We test the mediation effect of aspirational hope (using life aspirations as a key variable) on economic welfare (proxied by assets). We conduct the mediation analysis using the measures on which microcredit participation has significant direct effects. We perform the analysis following four steps below and estimate the standard errors of the corresponding equations using the bootstrapping method (with 1000 repetitions), according to the approach by Preacher & Hayes (2008). First, we estimate the effects of microcredit participation on the outcomes, as we do in equation (2). Second, we repeat this step for the mediators. Third, we test the correlation between outcomes and mediators. Fourth, we re-estimate equation (2), but this time including the mediator on the right-hand side of the equation. We then compare the coefficients measuring the impact of microcredit participation from the first and fourth step. If the coefficient is smaller in absolute terms from the last step, it suggests that mediation effects exist.

Table 5 shows the results, suggesting that life aspirations mediate effects on household durable assets. This might be in line with our previous findings that show stronger effects of microcredit participation on only one element of aspirational hope–aspirations–which seems to carry out the effects in this case. Overall, this descriptive evidence supports our theory of change.

Table 5 – Mediation analysis

	Household durable assets index (std)	Life aspirations (std)	Household durable assets index (std)	Household durable assets index (std)
	(1)	(2)	(3)	(4)
Uptake x Access	0.604***	0.478**		0.514**
	(0.191)	(0.239)		(0.204)
Uptake	-0.485***	-0.424*		-0.396**
	(0.187)	(0.254)		(0.191)
Access	-0.177**	-0.0438		-0.121
	(0.0902)	(0.102)		(0.0989)
Life aspirations			0.0684**	0.116***
			(0.0317)	(0.0288)
Controls	Yes	Yes	Yes	Yes
District dummies	Yes	Yes	Yes	Yes
Observations	1,148	1,120	1,106	1,106

Notes: Life aspirations and household durable assets index are standardized to a mean of zero and a standard deviation of one. Control variables are: age, adults, children (linear and square), Temne (tribe), and Muslim (religion). Bootstrapped standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Potential channels through which microcredit changes aspirations

On the basis of our theoretical framework, primarily by Ray (2006), we argue that there are two pathways through which microcredit might affect aspirations.

First, the group lending scheme with joint liability acts as a coordination device. Without this program, the women would not be able to borrow. Imagine a woman living in a community where few people have access to credit. Even if she has aspirations, she will not have the financial resources to reach them. Therefore, her aspirations for a better future will fade. However, group lending with joint liability might break this trap. Coordinated borrowing by the group represents an opportunity to realize their aspirations, which narrows the aspirations gap and creates a different equilibrium. As aspirations are socially determined (Ray, 2006), so they should be reinforced by the group lending methodology with joint liability. Every week, the group meetings bring together similar women from several small groups into a big group. These meetings improve their social interaction and connectedness, which potentially improve their aspirations by widening the aspiration window.

Second, group members can raise aspirations amongst each other. Several empirical studies (Beaman et al., 2012; Bernard et al., 2014; Lybbert & Wydick, 2017; Macours & Vakis, 2014, 2017) offer consistent evidence that leaders in communities serve as role models for other members. If role models are better off, women likely form a wider aspiration window, because they belong to the same groups and communities. In our study, the presidents of the small and big lending groups, who organize meetings and repayments, or the most well-off or successful members of the groups all may act as role models.

We test the pathways using information from 343 microcredit participants, organized into 22 big lending groups, from one of the BRAC office branches. Specifically, to measure social interaction and connectedness, we use three variables: (1) frequency of attendance at weekly meetings, measured from 1 = never to 4 = always; (2) walking distance to the weekly meeting place, measured in minutes; and (3) number of weekly meetings missed in the previous three months. We regress life aspirations of each group members on these three variables using ordinary least squares:

$$Y_{ij} = \delta_0 + \delta_1 F_{ij} + \sum_{h=1}^{H} \delta_h X_{ih} + \varepsilon_{ij}, \quad (3)$$

where Y indicates the life aspirations of woman i in group j; F represents the three variables measuring social interaction and connectedness of respondent i in group j; X is a vector of controls; and ε_{ij} is the error term clustered at the group level. As we show in Table 6, the more frequently members attend meetings, the higher are their life aspirations (0.314 points, 5% level). The farther away a member lives from the weekly meeting place, the lower her aspirations; when a member misses more weekly meetings, her life aspirations also are lower. The coefficients of these last two variables are not significant, but they exhibit the expected sign. Overall, this evidence suggests positive relationships of social interaction and connectedness with life aspirations.

To test for role model effects, we correlate member's life aspirations to that the life satisfaction (a proxy of wellbeing) of a role model (S_j), either the big group president's current level of life satisfaction[11] or the most well-off person in the group, using ordinary least squares:

$$Y_{ij} = \gamma_0 + \gamma_1 S_j + \sum_{h=1}^{H} \gamma_h X_{ih} + \varepsilon_{ij} \quad (4)$$

The results in Table 6 suggest that leaders with a higher level of life satisfaction have a modestly positive but not significant influence on the aspirations of group members. We find a significant and positive relationship between the most well-off person in the group and the life aspirations of other group members.

Table 6 – Life Aspirations

	Life aspirations (std)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Frequency attending meetings	0.282	0.314*								
	(0.180)	(0.180)								
Distance to meeting place			-0.006	-0.007						
			(0.008)	(0.008)						
Missed meetings in last 3 months					-0.014	-0.005				
					(0.065)	(0.065)				
Group president satisfaction level							0.057	0.052		
							(0.049)	(0.051)		
Person within the group with highest satisfaction									0.208*	0.219*
									(0.104)	(0.112)
Constant	8.277***	8.311***	9.343***	9.581***	9.293***	9.475***	8.832***	9.115***	7.495***	7.388***
	(0.711)	(0.887)	(0.141)	(0.500)	(0.0897)	(0.498)	(0.378)	(0.740)	(0.957)	(1.331)

[11] To measure current level of life satisfaction, we use the current level indicated on the cotton tree metric.

Control variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	316	301	326	311	325	309	268	254	295	280
R-squared	0.022	0.038	0.003	0.015	0.000	0.010	0.004	0.031	0.045	0.061

Notes: Life aspirations is standardized to a mean of zero and a standard deviation of one. Clustered (by group) standard errors, which are in parentheses. Control variables: age, adults, children (linear and squared), Temne (tribe), Muslim (religion). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Conclusions

This study provides an initial evaluation of the impact of microcredit on aspirational hope. We use identification strategies that rely on eligibility criteria established by BRAC, allowing access to microcredit only for those living within 4km from a branch office. We use matching to control for selection biases on observable variables and estimate the effects of microcredit access and participation. In addition, we consider a strategy that leverages a cross-sectional DID method to control for selection biases due to both observable and unobservable factors.

We first test whether microcredit has effects on both economic welfare and aspirational hope. Results from our preferred specification, the cross-sectional DID, shows that microcredit participation has positive and significant effects on household durable assets index, life aspirations and aspirational hope of future economic welfare. This evidence supports our first hypothesis regarding the positive effects of microcredit participation on aspirations. We find no support for our second hypothesis that microcredit participation increases respondent agency and pathways, possibly as our Trait Hope Scale does not capture the entire scope of pathways and agencies that can be enhanced by participation in a microcredit program.

Furthermore, we test the hypothesis that participation in a microcredit group lending scheme enhances economic outcomes partly through aspirations. A mediation analysis suggest that life aspirations indeed may mediate effects on household durable assets. However, we hasten to note that one should be careful with drawing causal claims from the mediation analysis due to potential problems with unobserved heterogeneity as the analysis assumes that there is no confounder affecting both the outcome and mediator variables.

We find that the positive relation between microcredit and life aspirations likely runs through two channels: (1) microcredit improves social interaction and connectedness, and (2) role models in lending groups increase the aspirations of other group members.

Overall, this study suggests that microcredit may play an important role in reducing internal psychological constraints and thereby provides an understudied channel by which microcredit helps to realize the SDGs. However, as our identification strategies do not fully control for potential sample selection biases, we stress, once again, that our results should be interpreted with caution. The evidence we provide is indicative and, in most cases, it is descriptive rather than causal. We also acknowledge potentially limited external validity of our study. We note that our results are not representative for the population of female borrowers all over the world, but they hold for female entrepreneurs in Sierra Leone.

Accordingly, we encourage further research to deepen the insights into the impact of microcredit on aspirational hope. More evidence about this causal relationship, as well as richer data to test the mechanisms driving the effects, all are required to draw clear conclusions.

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Appendices

Appendix 1. Inverse probability of treatment weighting (IPTW)

We use IPTW both for measuring impact of *access (A)* to microcredit as for measuring the impact of *uptake (U)* of microcredit. The method is the same in both cases. We explain the equations we used for measuring the impact of *access*, but similar equations apply for the impact of *uptake* (simply change *A* into *U*)

This method uses propensity scores to create weights and generate a pseudo-population in which the treatment assignment is independent of observable variables, as in randomization processes (Rosenbaum & Rubin, 1983). First, we estimate the probability (*P*) of having access to microcredit (*A*) over the total sample, conditional on the observed characteristics (*X*). We estimate the following equation and assume a logistic distribution:

$$A_i = \beta_0 + \beta_1 X_i + \varepsilon_i. \quad \text{(A1a)}$$

Second, we calculate stabilized weights (Robins, Hernán, & Brumback, 2000), which account for the proportion of women in the access area (numerator) and the inverse probability of having access to microcredit, conditional on the covariates (denominator). These weights are defined as $P(A = 1) / P(A = 1|X)$ for women in the access area and $(1 - P(A = 1)) / (1 - P(A = 1|X))$ for women in nonaccess area.

Third, using these weights, we conduct a balance test to determine if access and non-access areas are similar in observed characteristics. We estimate the following equation by weighted least squares (WLS):

$$X_i = \beta_2 + \beta_3 A_i + \varepsilon_i. \quad \text{(A2)}$$

Results

Microcredit access and participation using IPTW

Results of propensity scores from equation (A1). The values shown in Table A1 correspond to coefficient β_1 of the model. We present results both for the *access* model as well as for the *uptake* model.

Table A1 – Propensity Scores

Variables	Access	Uptake
Adults	-0.0115	0.0133
	(0.0479)	(0.0405)
Children	0.0458	0.206***
	(0.122)	(0.0718)
Children squared	-0.00193	-0.0125**
	(0.0121)	(0.00557)
Age	0.0213**	0.0261***
	(0.00932)	(0.00805)
Temne (tribe)	0.541***	0.226
	(0.172)	(0.158)
Muslim (religion)	0.560***	0.481***
	(0.177)	(0.166)
District 2	1.193***	2.491***
	(0.274)	(0.245)
District 3	0.547**	0.823***
	(0.262)	(0.224)
District 4	-0.215	0.190
	(0.228)	(0.192)
Constant	-0.280	-2.140***
	(0.436)	(0.376)
Observations	1,228	1,228
Area under ROC	0.7101	0.7719

Notes: Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Results of balance test from equation (A2). The values shown in Table A2 correspond to coefficient β_3 of equation A2.

Table A2. Balance test

Variables	N	Access	Uptake
Adults	1228	-0.0254	-0.110
		(0.198)	(0.195)
Children	1228	-0.180	-0.119
		(0.332)	(0.224)
Age	1228	-0.0486	0.126
		(0.802)	(0.736)

Temne	1228	-0.0392	-0.0319
		(0.0400)	(0.0358)
Muslim	1228	-0.0251	-0.0219
		(0.0299)	(0.0285)

Notes: Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. N: Number of observations.

Table A2 shows that after weighting, our variables are "balanced" both for *access* and *uptake*.

Appendix 2: the cross-sectional difference-in-difference model, and underlying assumptions/limitations.

In order to understand our DID approach, as well as the underlying assumptions, consider the following regression, equivalent to a DID model:

$$Y_{ij} = \beta_0 + \beta_1 A_j + \beta_2 U_{ij} + \beta_3 A_j \times U_{ij} + \mu_{ij},$$

where Y_{ij} is the outcome variable of woman i in region j, A_j is a binary variable indicating availability of the MFI (equal to 1 within the access area, and 0 otherwise); *U* is a binary variable equal to 1 if woman i in region j takes up microcredit (irrespective of whether an MFI is available) and μ_{ij} is the error term. β_0 is an intercept term; β_1, β_2, β_3, are fixed but unknown slope coefficients. β_3 is the DID coefficient: it determines the impact of the uptake of microcredit while controlling for differences between uptakers and non-uptakers and for living in an area where the MFI is available (access area) or the area where the MFI is not available (non-access area).

Note that the above equation is similar to equation 2 in the main text. For reasons of convenience, we ignored the controls. Moreover, we use "actual" uptake of microcredit (*U*), instead of "forecasted" uptake $\widehat{U}$, assuming that also for the non-access area we would know the women who would take up microcredit if an MFI would be available. However, this assumption will be relaxed below.

The disturbance term represents the net effect of variables omitted from the analysis. There is no problem if the above equation is in line with the process that generates the data. However, things become more complicated if we assume that unobservables differ by region (access versus non-access) and by status (uptake versus non-uptake). For instance, assume that part of the unobservables are specific to the region (access or non-access area) but are invariant over adopters and non-adopters (e.g., t_j); that others are specific to adopters' status (and would-be adopters') but invariant over the region (e.g., w_i); and that some are specific to both adopters' status and region (e.g., h_{ij}). In this case, we can write:

$$\mu_{ij} = t_j + w_i + h_{ij}.$$

This process gives us error terms for four groups (adopters versus non-adopters in access and non-access regions):

A) j=1 and i=1: $\mu_{11} = t_1 + w_1 + h_{11}$.

B) j=1 and i=0: $\mu_{01} = t_1 + w_0 + h_{01}$.

C) j=0 and i=1: $\mu_{10} = t_0 + w_1 + h_{10}$.

D) j=0 and i=0: $\mu_{00} = t_0 + w_0 + h_{00}$.

The DID procedure ensures that unobservables related to treatment status (w_i) and to the treatment area (t_j) difference out. However, it does not difference out error terms that are specific to both adopter status and region. Thus, double differencing results in the term ($h_{11} – h_{01}$) – ($h_{10} – h_{00}$), which only drops out if ($h_{11} – h_{01}$) = ($h_{10} – h_{00}$). Hence, a key assumption of our DID approach is that the difference between unobservables of adopters and non-adopters in the access area is the same as the difference between unobservables of would-be adopters and would-be non-adopters in the non-access area. This assumption is akin to the so-called *parallel trends* assumption for the

standard DID approach. In order to test the reliability of this assumption, we present so-called selection tests (see below).

Microcredit participation using cross-sectional difference-in-difference approach

As we don't know who is willing to take up microcredit in the non-access area if an MFI would be available, we have to estimate would be adopters and non-adopters in the non-access area. We do so by only using the sample of individuals in the access area, and estimate their propensity to uptake microcredit. We next conduct an out-of-sample forecast of expected participants and expected nonparticipants outside the access area. We also reclassify the actual microcredit adopters and non-adopters in the access area in predicted microcredit adopters and non-adopters in the access area.

Table A3 shows the model specification that predicts the propensity to participate among individuals in the access area. It shows that the number of children, age, and districts emerge are the main determinants of microcredit participation.

Table A3. Determinants of uptake in the access area

Variables	Uptake
Adults	0.0397
	(0.0529)
Children	0.305***
	(0.0975)
Children squared	-0.0195***
	(0.00746)
Age	0.0255**
	(0.0112)
Temne (tribe)	-0.0559
	(0.212)
Muslim (religion)	0.255
	(0.229)

District 2	3.778***
	(0.564)
District 3	0.773***
	(0.283)
District 4	0.430*
	(0.221)
Constant	-1.564***
	(0.498)
Observations	1,012
Area under ROC	0.7993

Notes: Bootstrapped standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

To measure the accuracy of our model in terms of predicting the propensity to uptake microcredit, we calculate the area under the receiver operating characteristic (ROC) curve (AUC). If AUC equals 1, the model perfectly classifies participants and nonparticipants; an AUC equal to 0.50 does not discriminate between the two groups (Zweig & Campbell, 1993). The AUC of our model equals 0.7993, which indicates that it performs well in classifying participants versus nonparticipants.

To identify expected borrowers and nonborrowers, we need to establish a threshold participation probability, above which a woman is classified as a participant. We use four different methods to find the optimal cutoff point. The most straightforward method uses a cutoff point at 0.5, but it only correctly classifies 53% of participants and nonparticipants in the access area. Three other methods appear commonly in epidemiology literature to find an optimum cutoff point: the Youden (1950) index method, which maximizes the difference between sensitivity and specificity; Liu's (2012) method, which maximizes the product of sensitivity and specificity; and the nearest to (0,1) method, which minimizes the Euclidean distance between the ROC curve and the (0,1) point, that is, the point on the ROC curve closest to the (0,1) point (Perkins & Schisterman, 2006).

We set the optimal cutoff point, according to two criteria: (1) the number of individuals correctly classified, and (2) the smallest difference between sensitivity and specificity because we are interested in correctly classifying participants and nonparticipants. Table A4 shows this information for each cutoff point.

Table A4 – Cutoff Points

	0.5	Liu	Youden	Nearest to (0,1)
Cutoff point	0.5	0.7660	0.8085	0.7472
Sensitivity at cutoff	98%	64%	56%	67%
Specificity at cutoff	8%	83%	93%	79%
Correctly classified	53%	74%	75%	73%

We find that the threshold of 0.7472, derived from the nearest to (0,1) method, is the optimal, because it classifies 73% of the women in the access area. The new sample frame estimated with this threshold is presented in Table A5.

Table A6 – Predicted Sample Frame

	Access area (Inside 4 km radius)	Non-access area (Outside 4 km radius)	Total
Eligible participants	581	65	646
Eligible nonparticipants	431	151	582
Total	1012	216	1228

Selection tests

As we have explained above, we use so-called selection tests to test one of the main assumptions of our approach. We perform selection tests using our predicted sample frame (see above), and hence forecasted participation values instead of actual participation levels. The selection tests then come down to estimating the following equation for each control variable X:

$$X_{ij} = \vartheta_0 + \vartheta_1 A_j + \vartheta_2 \widehat{U}_{ij} + \vartheta_3 A_j \times \widehat{U}_{ij} + \varepsilon_{ij},$$

where X is a vector of observed characteristics of women; $\widehat{U}$ is a binary variable equal to 1 if woman i is (re)classified as a participant, and 0 otherwise; and ε_i is the error term. Our coefficient of interest is ϑ_3. A non-significant coefficient indicates that the selection process is similar in the access region and the non-access region. The results of the selection tests are presented in table A6.

Table A6. Selection Test

	Adults	Children	Children squared	Temne (tribe)	Muslim (religion)
(Forecasted) Uptake x Access	-0.261	-0.393	-0.522	-0.00484	-0.0854
	(0.325)	(0.371)	(1.226)	(0.0798)	(0.0700)
(Forecasted) Uptake	1.073***	2.267***	5.480***	0.132*	0.202***
	(0.305)	(0.345)	(1.111)	(0.0737)	(0.0650)
Access	0.115	0.259*	0.606	0.175***	0.153***
	(0.138)	(0.134)	(0.722)	(0.0464)	(0.0455)
Constant	2.974***	2.656***	30.78***	0.391***	0.583***
	(0.117)	(0.101)	(0.633)	(0.0398)	(0.0402)
Observations	1,228	1,228	1,228	1,228	1,228

Notes: Bootstrapped standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Limitations

One of the main underlying assumptions of our DID approach is that the selection process is similar in the access and non-access area. Our selection tests, presented in table A.6 above, provide some confidence in the reliability of this assumption. However, our approach is subject to some other limitations which we discuss here.

First, we acknowledge that our control group is small, which reduces the precision of our estimates. One of the main causes of this problem is that we had to sample women in the non-access area, who do meet the eligibility requirements (except for the distance to the branch).

The second main limitation arises from the fact that, unlike Coleman (1999), we do not have information about the willingness of women in the non-access area to take up. Thus we had to predict participants, using observable characteristics of women in the access area. It is unclear to what extent this procedure biases our results. However, in order to reduce potential biases, we e.g. determined standard errors using a bootstrapping approach. Specifically, we simultaneously estimated the outcome equation and the uptake equation, and bootstrapped the entire process. We also used "predicted" participants for the access area in the outcome equation.

Another potential limitation may be due to spillover effects. It is possible that women in the non-access area somehow benefited from the microcredit program. Even though our dataset does not allow to test or control for spillovers, it seems likely that if spillovers exist, the measured impacts of microcredit will be biased downwards.

Placebo test

In order to further test the reliability of our approach, we perform a placebo test, we (1) randomly split women in the access area into participants (50%) and non-participants (50%), (2) repeat all the steps of the DID approach (indicated above): estimating the uptake model and the cutoff, predicting uptake in the access and non-access areas and estimating the impacts using the predicted sample. As the (expected) treatment in the non-access area is now randomly assigned, one would expect that uptake of microcredit using our DID approach (equation 2 in the main text) would not lead to any significant effects.

Table A7 below presents the results of this approach. The table shows that for none of the outcome variables the coefficient for the interaction terms is no significant, which provides some additional support for our approach.

Table A7. Placebo Test –Impacts of Microcredit Participation Using Cross-Sectional DD

			Aspirational hope			Economic welfare	
	Agency and pathways index	Life aspirations (std)	Life aspiration gap (std)	Monthly income in good year (log)	Monthly income in bad year (log)	Monthly income current month (log)	Household durable assets index (std)
Uptake x Access	-0.569	-0.181	-0.272	0.189	0.0689	0.314	0.179
	(0.426)	(0.272)	(0.243)	(0.253)	(0.257)	(0.268)	(0.308)
Uptake	0.176	0.213	0.206	-0.185	-0.0620	-0.246	-0.254
	(0.466)	(0.260)	(0.243)	(0.249)	(0.251)	(0.269)	(0.295)
Access	-0.0443	0.177	0.111	0.0297	0.149	0.106	-0.0250
	(0.239)	(0.155)	(0.116)	(0.123)	(0.126)	(0.133)	(0.144)
Constant	0.0913	-0.110	-0.305	12.94***	12.16***	12.89***	-0.158
	(0.424)	(0.230)	(0.206)	(0.213)	(0.220)	(0.214)	(0.226)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,161	1,120	1,118	1,165	1,165	1,106	1,148

Notes: Life aspirations, life aspirations gap, and household durable assets index are standardized to a mean of zero and a standard deviation of one. Monthly income in good and bad year and monthly income of current year are presented in their logarithmic transformation. Control variables are: age, adults, children (linear and square), Temne (tribe), and Muslim (religion). Bootstrapped standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.