Economica

Economica (2022) **89**, S239–S275
doi:10.1111/ecca.12424

Microfinance and Diversification

By Oriana Bandiera*, Robin Burgess*, Erika Deserranno†, Ricardo Morel‡, Imran Rasul§, Munshi Sulaiman¶ and Jack Thiemel*

**LSE* *†Northwestern* *‡IPA* *§UCL* *¶BRAC/BIGD*

Final version received 18 March 2022.

The bulk of the world's extreme poor work in subsistence agriculture. Diversification out of this activity is often seen as the *sine qua non* of economic development. We evaluate whether the roll-out of a mainstay development intervention—microfinance—into poor, agricultural and largely unbanked populations in rural Uganda helps borrowers to diversify into non-agricultural labour activities. The new microfinance product is targeted to women, and differs from existing sources of formal and informal credit in that it allows them to borrow larger amounts but has inflexible repayment dates and the use of funds is monitored. We find that the arrival of microfinance enables women to diversify out of agriculture and into service-based activities such as small-scale trading. This low-level structural change, however, is not transformative in that it does not lead—at least after two years—to significant uplifts in earnings, consumption, savings, investment and overall wealth.

Introduction

The bulk of the extreme poor (those living on less than $1.90 a day) reside in rural areas of Africa and South Asia, and work mainly in subsistence agriculture (World Bank 2021). Their poverty belies both a lack of physical and human capital, and a low return to their labour. In addition, they suffer idiosyncratic and aggregate shocks stemming from climate, pests and health of persons and livestock. In such settings, the focus of policy falls naturally on how to encourage households to diversify out of subsistence agriculture into higher-return and more stable labour market activities. Indeed, when viewed through the lens of macroeconomic outcomes, this is the *sine qua non* of the economic development process (Buera *et al.* 2021).

But how to encourage this process is less than clear. One key observation is that the extreme poor engaged in subsistence agriculture are typically rationed out of formal credit markets and tend to rely on informal transfers and credit, that while flexible, are small-scale and essentially focused on insurance purposes (Udry 1994). These are useful for smoothing consumption but may have limited leverage in terms of changing employment and production activities (Balboni *et al.* 2021). Part of the problem here is that the low, variable and infrequent returns that characterize subsistence agriculture are not attractive to formal lenders. Therefore it is the agriculturally engaged extreme poor who are most in need of diversification yet are also the least able to avail themselves of formal finance.

It is in this context that the promise of microfinance shines through. It has become a cornerstone of development interventions from NGOs and government precisely because it is seen as capable of reaching and providing finance to the poorest households, offering them large enough loans with the aim of pushing forward productive investments that can help them to diversify out of subsistence agriculture and pull them out of poverty (Banerjee and Duflo 2011; Banerjee *et al.* 2015a). As Buera *et al.* (2020) report, between 1997 and 2013, access to microfinance grew by 19% per year, with the Microcredit Summit Campaign reporting over 3000 microfinance institutions (MFIs) serving over 200 million borrowers as of 2016.

Has microfinance fulfilled this promise? We contribute to answering this question by evaluating the entry of a group-based microfinance product into rural Western Uganda, by the NGO BRAC. Our context is one where close to 50% of our study population resides below the $1.90 extreme poverty cut-off, and over 80% are engaged in subsistence agriculture. It is also a setting where there has been limited penetration of formal financial institutions. It is thus fairly archetypal of rural areas across Africa where the remaining extreme poor in the world are becoming concentrated (Page and Pande 2018). Such settings, with a slow pace of structural change, are among the most difficult for MFIs to penetrate; it is an interesting and important question to discover whether these products can engender diversification out of agriculture and improve welfare.

The BRAC microfinance product that we study was first developed in Bangladesh (where BRAC is one of the top three providers of microfinance as measured by number of borrowers) and has been adapted for use in Uganda. Between BRAC's entry in 2006 and our endline in 2014, BRAC became the largest provider of microfinance not just in Uganda but in Sub-Saharan Africa as a whole. BRAC microfinance groups comprise women-only borrowers. We measure impacts on labour activities, earnings, consumption, savings, investment and a proxy for overall welfare in a sample tracking 4000 women over a two-year period, using a randomized control trial where half the villages are randomized to receive the new microfinance product.

The BRAC microfinance product, which now forms the backbone of BRAC operations across Africa, was designed to encourage diversification of household earning streams. Offered loan sizes are large relative to other available credit sources in rural Uganda, and are intended to enable women to begin or expand non-agricultural labour activities. To qualify for a loan, a borrower needs to demonstrate that the proposed investment is viable and will enable them to make weekly repayments. There is also some monitoring of the use of the loan after it is granted. Thus though the BRAC microfinance product shares many features of other products—in terms of targeting women micro-entrepreneurs, group lending, absence of collateral requirements, and frequent and inflexible repayment schedules—what sets it apart are the magnitude of the loans, the screening requirements and the monitoring of loan use.

This is made precise in Tables 1, where we provide a comparison of the features of the microfinance product that we evaluate, to those from other prominent evaluations. We return to this comparison throughout.

Our first stage of analysis considers households' engagement in credit transactions pre-intervention, and the pre-existing credit sources available to households. Unsurprisingly, we find that informal borrowing is far more prevalent than expected: 24% of households report having borrowed from some informal source. Households are as likely to borrow from family/friends as they are to borrow from local savings cooperatives. In contrast, 5% of households report ever having borrowed from some formal source—such as a bank, another MFI or an NGO. Each source of informal and formal finance that households have access to offers credit on differing contractual structures. Multiple sources of credit can coexist in the same village economy if households vary in their demand for credit in terms of the amounts demanded, flexibility of repayments, and so on. Microfinance—with its inflexible repayment structures—is not well suited for those engaged solely in agriculture given that earnings streams tend to be volatile and bunched at certain times of the year. Hence the focus of BRAC and other MFIs on credit provision targeting micro-entrepreneurship.

This has two implications for our analysis. First, the entry of BRAC into these credit markets represents evaluating the impact of increased access to microcredit, not the impact of introducing access to credit altogether. The extent to which BRAC microcredit simply causes households to substitute away from pre-existing credit sources that offer similar terms reduces the *net* economic impacts of BRAC microloans between treated and control villages. Second, comparing credit product characteristics, we should expect non-random selection

TABLE 1, PART 1
OVERVIEW OF MICROCREDIT INTERVENTIONS AND EVALUATIONS

	This study (1)	Banerjee *et al.* (2015b) (2)	Tarozzi *et al.* (2015) (3)	Angelucci *et al.* (2015) (4)	Attanasio *et al.* (2015) (5)	Crépon *et al.* (2015) (6)	Augsburg *et al.* (2015) (7)	Karlan and Zinman (2011) (8)
Panel A: Context								
Region	Uganda	India	Ethiopia	Mexico	Mongolia	Morocco	Bosnia and Herzegovina	Philippines
Year	2014	2007	2006	2010	2008	2007	2009	2007
Rural or urban?	Rural	Urban	Rural	Both	Rural	Rural	Both	Urban
Baseline borrowing from banks	0.8%	3.6%	2.6%	28.8%	47.7%	2.0%	51.4%	No data
Panel B: Borrowers								
Gender of borrowers	BRAC provides credit only to women	Women only	All	Women only	Women only	All	All	All
Targeted to microentrepreneurs?	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Loan eligibility	Women aged 20–50; only one member per household; must have lived in area 3–5 years (so not recent incoming migrant); must not be client of another MFI; live within 4 km of local BRAC branch office.	Women aged 18–59, resided in same area for at least 1 year, have valid identification and residential proof (at least 80% of women in group must own their home).	Poverty status, viable business plan, and other criteria.	Women aged 18–60 with proof of address and valid identification.	Women who own less than MNT 1 million ($869 exchange rate) in assets and earn less than MNT 200,000 ($174 exchange rate) in monthly profits from business.	Men and women aged 18–70, hold national ID card, have residency certificate and have had economic activity other than livestock agriculture for at least 12 months.	Sufficient collateral, repayment capacity, credit worthiness, business capacity, credit history, other (including characteristics). ****	18–60 years old; in business for at least 1 year; in residence for at least 1 year if owner, or at least 3 years if renter; daily income at least 750 pesos.

TABLE 1, PART 1
(CONTINUED)

	This study (1)	Banerjee *et al.* (2015b) (2)	Tarozzi *et al.* (2015) (3)	Angelucci *et al.* (2015) (4)	Attanasio *et al.* (2015) (5)	Crépon *et al.* (2015) (6)	Augsburg *et al.* (2015) (7)	Karlan and Zinman (2011) (8)
Panel C: Loans								
Liability	Group (joint liability)	Group (joint liability)	Group (joint liability)	Group (joint liability) or individual	Group (joint liability)	Group (joint liability)	Individual	Individual
Group size	15–30 members	6–10 people	No data	10–50 people	7–15 people	3–4 people	No data	No data
Loan term	20 weeks or 40 weeks	12 months	12 months	4 months	6 months average for group, 8 months average for individual	16 months average	14 months average	No data
Repayment frequency	Weekly, beginning second week of loan disbursement	Weekly	Borrower expected to make regular deposits and repayments	Weekly	Monthly	Weekly, twice weekly or monthly	Monthly	No data
Interest rate	40-wk loan: 40% APR	24% APR (12% non-declining)	12% APR	110% APR	26.8% APR	14.5% APR	22% APR	63% APR
Loan size	554.93 (2014 USD PPP)	1031 (2014 USD PPP)	Median 624 (2014 USD PPP)	570 (2014 USD PPP)	854 group (per borrower); 1258 individual (2014 USD PPP)	1623 (2014 USD PPP)	2750 (2014 USD PPP)	Median 711 (2014 USD PPP)
Loan size/GDP per captita	0.267	0.165	0.986	0.031	0.077 (individual), 0.11 (joint)	0.198	0.215	0.124

TABLE 1, PART 2
OVERVIEW OF MICROCREDIT INTERVENTIONS AND EVALUATIONS

	This study (1)	Kaboski and Townsend (2012) (9)	Maitra *et al.* (2017) (10)	Fiala (2018) (11)	Cai *et al.* (2020) (12)	Beaman *et al.* (2020) (13)	Crépon *et al.* (2020) (14)	Bryan *et al.* (2021) (15)
Panel A: Context								
Region	Uganda	Thailand	India	Uganda	China	Mali	Egypt	Egypt
Year	2014	2001	2007	2012	2010	2010	2016	2016
Rural or urban?	Rural	Both	Rural	Semi-urban	Rural	Rural	Rural	No data
Baseline borrowing from banks	0.8%	No data	5%	No data	13%	No data	No data	No data
Panel B: Borrowers								
Gender of borrowers	BRAC provides credit only to women	All	All	All	All	Female	All	All
Targeted to microentrepreneurs?	Yes	No	No	Yes	No	No—farmers	Yes	Yes
Loan eligibility	Women aged 20–50; only one member per household; must have d lived in area for 3–5 years (so not recent incoming migrant); must not be client of another MFI; live within 4 km of local BRAC branch office.	All villages eligible for Million Baht Village Fund injected potential funds into 77,000 heterogeneous Thai villages;each transfer used to form independent village bank for lending within village.	Less than 1.5 acres of land. TRAIL (trader recommended borrowing arm): trader recommended 30 borrowers, 10 randomly selected. GBL: two five-member groups formed out of those who were also successful in keeping savings account with MFI for previous 6 months.	Surveyed 4630 Central and North Uganda; districts selected 1550 individuals willing to take loan and interested in ILO training; divided these into five groups of treatment and control with combinations of grants, loans and training.	Collateral required for individual liability; group liability (5–7 people) need not be with collateral; for eligibility, over 18, only one member of household can become member; need to fill application and pay membership fees (refundable if no default); poor households given priority.	Loan product designed for women farmers, organized into associations (JL groups); loans dispersed at beginning of season and collected at end; informal application process.	Be aged 21–35; submitting basic business plan; screening by NGO; randomization. Also had training component, experienced businesspersons allowed to exit.	Existing clients of partner MFI shortlisted based on information with loan officer; this shortlist fills up loan application used by central credit committee to make final decisions (based on borrowers' repayment of at least three prior loans).

TABLE 1, PART 2
(CONTINUED)

	This study (1)	Kaboski and Townsend (2012) (9)	Maitra *et al.* (2017) (10)	Fiala (2018) (11)	Cai *et al.* (2020) (12)	Beaman *et al.* (2020) (13)	Crépon *et al.* (2020) (14)	Bryan *et al.* (2021) (15)
Panel C: Loans								
Liability	Group (joint liability)	NA	Individual vs. joint	Individual	Individual and groups (joint liability)	Group (joint liability) in practice	Individual	Individual or firm
Group size	15–30 members	NA	5 for GBL	NA	5–7 for group	30	NA	NA
Loan term	20 weeks or 40 weeks	NA	4 months	12 months	12 months	4–6 months	No data	12 months
Repayment frequency	Weekly, beginning second week of loan disbursement	NA	Lump sum after 4 months	Monthly	Yearly	Lump sum at end	No data	Monthly
Interest rate	40-wk loan: 40% APR	NA	18% APR	20% APR	9.4% APR	25% APR	15–24%	14–17% APR
Loan size	554.93 (2014 USD PPP)	NA	206 (2014 USD PPP)	No data	1266 (2014 USD PPP)	159 (2014 USD PPP)	No data	7522 (2014 USD PPP)
Loan size/GDP per captita	0.267	NA	0.05	No data	0.14	0.09	No data	0.71

TABLE 1, PART 3
OVERVIEW OF MICROCREDIT INTERVENTIONS AND EVALUATIONS

	This study (1)	Banerjee *et al.* (2015b) (2)	Tarozzi *et al.* (2015) (3)	Angelucci *et al.* (2015) (4)	Attanasio *et al.* (2015) (5)	Crépon *et al.* (2015) (6)	Augsburg *et al.* (2015) (7)	Karlan and Zinman (2011) (8)
Panel D: Evaluations								
Sampling frame	Households with at least one woman aged 20–50 that have business or economic activity and have resided in area for 3–5 years.	Households with at least one woman aged 18–55 that have resided in same area for at least 3 years.	Random selection of households.	Mexican women aged 18–60 who have business/economic activity, would start one if had enough money, or would consider taking credit from an institution.	Women who met eligibility criteria and signed up to declare interest in receiving loan from lender.	Households deemed likely borrowers; random selection of households.	Marginal loan applicants considered too risky and ‘unreliable’ to be offered credit as regular borrowers under terms above.	Marginal loan applicants randomly assigned to eligible and ineligible by algorithm.
Samples	4088 households, 121 villages	6863 households, 52 clusters	6412 households, 162 villages	16,560, 238 clusters	1148, 40 villages	4465 households, 81 villages	1196 marginal loan applicants	1601 marginal loan applicants
Panel	Yes	No	No	Partial	Yes	Yes	Yes	No
Randomization	Across clusters	Across clusters	Across clusters	Across clusters	Across clusters	Across clusters	Across individuals	Across individuals
Panel E: Results								
Diversification into SE	Yes	No	No	No	Yes	No	No	No
Welfare	No	No	No	Yes; for 2 out of 6 indices (depression and fire sales of assets)	Yes; food consumption, per capita consumption	No	No	No

TABLE 1, PART 4
OVERVIEW OF MICROCREDIT INTERVENTIONS AND EVALUATIONS

	This study (1)	Kaboski and Townsend (2012) (9)	Maitra *et al.* (2017) (10)	Fiala (2018) (11)	Cai *et al.* (2020) (12)	Beaman *et al.* (2020) (13)	Crépon *et al.* (2020) (14)	Bryan *et al.* (2021) (15)
Panel D: Evaluations								
Sampling frame	Households with at least one woman aged 20–50 that have business or economic activity and have resided in area for 3–5 years.	Townsend Thai dataset.	For both TRAIL and GBL villages, 50 households surveyed; 10 in each given loans (treated); 10 others Control 1, randomized out; final 30 Control 2, chosen randomly from villages.	Random sample from larger survey in North and Central Uganda.	In each county, Ministry listed 5 poor villages and study assigned 3 to treatment and 2 to control.	Stage 1: villages divided into loan and grant villages (because larger aim is to study selection effect when giving loans). Stage 2: ones not given loans in loan villages given grants.	Those interested in taking a loan randomly assigned to three treatment arms (in-kind, grant, loan) and a control, after fulfilment of basic criteria.	From all applicants that fit screening criteria, some given twice their previous loan (control) and others four times (treatment); stratified at the loan-officer level.
Samples	4088 households, 121 villages	960 households in 64 rural and semi-urban areas	2070 households, 48 villages	1500 individuals	1222 households, 45 villages, 9 counties, 5 provinces	6807 individuals, 198 villages	3294 individuals	1004 borrowers
Panel	Yes	Yes	No	Yes	No	Yes	No	Yes
Randomization	Across clusters	Not an RCT	Across clusters	Across individuals	Across clusters	Across clusters	Across clusters	Across clusters
Panel E: Results								
Diversification into SE	Yes	No	No	No	No	No	Yes	No
Welfare	No	Yes, short term; consumption, wages, income	Yes; farm incomes (TRAIL only)	No	Yes; income, wellbeing index; poverty reduction	No	Yes; quality of life, profits	Yes; household income

into BRAC microfinance groups and the take-up of the offer of credit. Those borrowing from BRAC rather than other sources might be positively selected in that they demand more credit but are willing to take on such loans despite the inflexible timing of repayment and higher interest rates.

We focus on presenting intent-to-treat (ITT) estimates. We also discuss treatment-on-the-treated (TOT) estimates for BRAC borrowers (suitably heavily caveated given the potential existence of within- and across-village spillovers from the entry of BRAC, and the potential for heterogeneous treatment effects).

On diversification in labour activities, we document ITT (and TOT) effects showing that women diversify away from subsistence agriculture towards self-employment (SE) in service-based non-agricultural work. The programme was thus successful in encouraging micro-entrepreneurship. Pre-intervention, around 20% of women engaged in some non-agricultural work. Among those, 45% are engaged in small-scale trading, and 17% own and run a shop or restaurant. Small-scale trading covers a whole range of activities, such as door-to-door selling and selling food and beverages, textiles and clothing, agricultural inputs and other products in local markets. These are business activities that typically do not involve any physical structure or employees. Shops and restaurants, in contrast, require a physical structure and may involve employees. We find that BRAC borrowers tend to shift into exactly such small trade forms of non-agricultural employment, thus emulating activities that were already taking place in the village.

On the intensive margin, we find that women spend significantly more hours working in non-agricultural activities. This is accompanied by a reduction in hours working in agriculture. The combined labour supply estimates across both activities suggest that the total labour supply of borrowers remains unchanged at least over the two-year study period.

We document very imprecise (and statistically insignificant) treatment effects on women's earnings, either in aggregate or by labour activity, although BRAC borrowers are significantly more likely to generate positive earnings in the non-agricultural work that they switch into or expand. The fact that even for non-agricultural labour, earnings impacts activities remain imprecise, might also be partly due to the concentration of women into just a few types of non-agricultural activities.

On credit transactions with non-BRAC sources, we find relatively precise null impacts on borrowing from these alternative sources. Hence BRAC microloans are neither complements nor substitutes for other credit sources. This perhaps implies that women no longer remain credit-constrained after having access to BRAC microloans, consistent with the scale of loans on offer being far larger than available from other credit sources. Reassuringly, the result is also consistent with households not entering debt traps because they need to engage in further borrowing in order to pay off existing loans.

Our final set of outcomes considers how the patterns of diversification into non-agricultural labour activities translate into other economic aggregates related to consumption, savings, asset accumulation and welfare. We find null impacts on total and food consumption, although the point estimate on the value of food expenditure (including implicitly valuing home-produced food) is positive and large. Breaking down consumption into various components, we also find no precise impacts on discretionary spending, spending on durables, or spending on health or education. Nor do we find precise impacts on savings, asset accumulation or the overall wealth score of households, proxying their permanent income.

Our finding of effects on diversification but with no effects on welfare places the results of this study somewhere between the bulk of the microcredit literature (see Table 1, where we review 14 randomized evaluations), which finds effects on neither, and the big push asset and cash transfer programmes that involve larger transfers and find effects on both (Blattman *et al.* 2014; Jack *et al.* 2016; Bandiera *et al.* 2017; Bari *et al.* 2021).

Our finding on diversification towards non-agricultural labour market activities runs counter to the main body of research on microfinance (Table 1). Of the 14 papers that we review in Table 1, only two find diversification into self-employment (Attanasio *et al.* 2015; Crépon *et al.* 2020). Both studies, like ours, study microfinance in a rural context, but in countries, Mongolia and Egypt, that are both approximately five times richer than Uganda in terms of GDP per capita. The Mongolia project also had a much more developed credit market at baseline, as evidenced by the large share of people borrowing from rural banks.

The small and null effects that we find on welfare, however, are consistent with the main body of research focused on randomized evaluations of microfinance programmes (see Table 1), and are also consistent with earlier non-randomized evaluations of microcredit (Morduch 1999). The established body of evidence of microfinance research reviewed in Table 1 finds small or marginal average treatment effects on business outcomes, the most common of which is the expansion of existing businesses. However, these studies find that effects of microfinance rarely feed through into higher consumption, investment or permanently drawing households out of poverty (Banerjee 2013; Banerjee *et al.* 2015a). We show in Table 1 that even for papers that find improvements in welfare, the results are not present across the full range of indicators. There is a consensus that at least for the average borrower, these effects are not transformative, with meta-analysis such as Meager (2019) concluding that for household business and consumption variables, the effect of microfinance may be negligible. Explanations of why the intent-to-treat estimates in this literature have wide confidence intervals (which cannot rule out economically meaningful improvements in economic wellbeing)—which also applies to our study—include low take-up rates, spillovers into controls, heterogeneous treatment effects, and the fact that monetary outcomes are often difficult to measure without error.

The remainder of the paper is organized as follows. Section I describes the microfinance programme and our data, design and empirical approach, and presents evidence on credit markets in these rural economies. Section II presents our results on take-up, labour activities, earnings, credit and economic aggregates. Section III concludes. The Appendix discusses research ethics.

I. Intervention, Data and Design

Context

The majority of the world's poor rely on the agricultural sector as their chief source of labour market earnings. Yet agricultural productivity remains low in many developing regions, especially in Sub-Saharan Africa. Some persistent causes are low adoption rates of improved and high-yielding seed varieties, and limited use of modern agricultural techniques (Evenson and Gollin 2003; World Bank 2008). Microfinance is likely to have limited impacts on easing such constraints related to market innovation and farmers' information sets. However, credit can aid households' movement out of poverty by enabling some of their members to change labour activities on the extensive margin, switching effort and resources away from low return and volatile earnings streams in agriculture, towards forms of self-employment that are more capital-intensive and potentially offer higher and more stable returns. This diversification of household earning streams and movement towards more capital-intensive labour activity is the inherent process of structural change that lies at the core of the literature at the nexus of entrepreneurship, credit markets and economic development (Banerjee and Newman 1993; Buera *et al.* 2015; Bandiera *et al.* 2017).

Our study context—rural Uganda—remains largely unbanked, and households have low rates of access to financial services, as in most other countries of Sub-Saharan Africa. According to a nationally representative survey conducted by FinScope Uganda (2009), 71% of the population lacked access to bank or formal services in 2009. The same survey reported that 43% of households met their financial needs from informal sources such as friends and relatives.

The rural credit market intervention that we evaluate is implemented by BRAC, one of the largest microfinance and development organizations in the world. BRAC first started its operations in Bangladesh, and has now become established within East Africa and Uganda in particular, as a major provider of credit to rural households. BRAC initiated its microcredit programme in Uganda in 2006, with a rapid within-country scale-up to reach over 100,000 households across more than 40 districts by 2010, just prior to our intervention (Sulaiman 2011). BRAC's credit market intervention is designed to facilitate micro-entrepreneurship among women, and thus targets women who are engaged in some form of income generating activity to begin with. The intervention purposefully aims to shift them away from subsistence agriculture by enabling them to either upscale agricultural production or switch to more productive forms of income-generation labour activity altogether. We examine the take-up and economic impacts of the roll-out of this programme into rural villages in two districts in Western Uganda: Kabale and Rukungiri.

The microfinance programme

The intervention is implemented at the village level (hence that is also our unit of randomization) and offers individual women large-scale microloans. BRAC monitors the use of loans to ensure that they foster entrepreneurship and enable borrowing households to diversify their earning sources. The programme is implemented by BRAC loan officers, who were recruited specifically for the expansion of the microfinance product into these two districts in Western Uganda. Loan officers are tasked to form microfinance groups in villages within their programme territory, discuss business ideas with clients, and help them to formulate business plans at the point of loan application. Post-disbursement, their role involves monitoring the use of funds, collecting weekly payments and following up clients who have not made repayments. Loan officers are paid a fixed monthly salary with a small bonus if they meet their disbursement and collection targets.

To select borrowers, BRAC uses a mix of survey and local consultations. After selection of a site for a BRAC branch, a census is conducted in all the villages located within a 4 km radius of the branch location. This gathers information on household assets and economic activities. This list is presented to the Local Council Chairperson (an elected government representative present in each village) to categorize households into poor and non-poor, using a variety of criteria such as holding of land and other assets, and using their deep local knowledge. Concurrently, BRAC makes an assessment as to whether a particular village is a viable proposition for forming a microfinance group based on the depth of business activity, cash economy and connection to markets. Based on this categorization and the asset and business activity information, both villages and particular households within them are marked as target clients.

BRAC prefers giving loans to women who currently have a business, but this is not a mandatory requirement. Members are approved a loan if the loan officer finds the business proposal and overall financial situation to be reasonable in terms of the ability to repay weekly installments. Hence BRAC loans can be used to allow borrowers to diversify through changes in extensive margin labour activities out of subsistence agriculture, or to scale up existing micro-entrepreneurial activities. Any household already participating in a credit programme of other MFIs is considered ineligible.

Once the set of eligible households is identified, BRAC staff convene a meeting of female members of these households aged roughly between 20 and 50, where the credit programme is explained. If around 10–15 women express interest, then they form a microcredit group in that village, and this is then split into five-member subgroups that meet on a weekly basis with the loan officer.

New members can join once a group is formed, meaning that initially non-eligible women can join if they want to and existing members are willing to accept these new members. It is also possible that women residing in neighbouring villages could join groups, including those from control villages in our evaluation sample. Members are added in groups of five, which means that microfinance groups end up comprising 15–25 members.

Loan sizes range from \$100 to over \$1000; the average loan disbursed is \$550. GDP per capita was around \$800 in 2012, when we collected our baseline data. As we document later, the available loan sizes from BRAC, however benchmarked, represent a potentially far larger big push injection of credit to households than is available from other sources in these villages.

Group members can begin to apply for loans after having been to three consecutive weekly group meetings, conditional on having received support from everyone else in the five-member subgroup. Following application, the loan officer and BRAC branch manager either assess business plans or conduct an enterprise visit where they physically observe the enterprise for which credit is being sought. They conduct a feasibility assessment of the loan amounts by collecting information on pre-loan sales and profitability of the existing business as well as other income sources. Loans begin to be disbursed after four weeks of regular attendance in weekly group meetings. A BRAC loan officer will typically visit borrowers multiple times to check how businesses are running and whether the repayment schedule can be met. These issues are also discussed in the weekly meetings.

Loans are provided on either 20- or 40-week cycles, with the large majority opting for the 40-week loans. Repayment schedules are frequent: repayments occur weekly (at weekly meetings of members), beginning the fortnight after the loan is disbursed.[1] Borrowers receive 90% of the approved loan, and the remaining 10% is kept as a security deposit that they can withdraw at completion of repayment or adjust as security deposit of their subsequent loans. The annual effective interest rate is around 40%; while this is high relative to other sources of finance, the marginal returns to microenterprise expansion has also been documented to be very high in similar contexts in the literature on capital drops to small and medium-sized enterprises (McKenzie and Woodruff 2008; Fafchamps *et al.* 2014), although other studies find far more limited returns on the margin (Karlan and Zinman 2012; Berge *et al.* 2015). Finally, BRAC microcredit groups did not provide any savings service during the evaluation period, so that the only financial incentive to join a group is in order to take out a loan. Hence we draw no distinction between group members and borrowers.[2]

Loans are provided to individuals, but group liability is enforced among five-member subgroups. In practice, group liability tends to be used primarily to provide security and exert peer pressure to ensure repayment, and avoid social and political incentives distorting the allocation of credit (Maitra *et al.* 2017, 2021; Bandiera *et al.* 2021; Vera-Cossio 2021).[3]

Comparison to other studies

To better understand where this microfinance product lies in the wider landscape of credit services evaluated in the literature, Table 1 compares various characteristics of our intervention

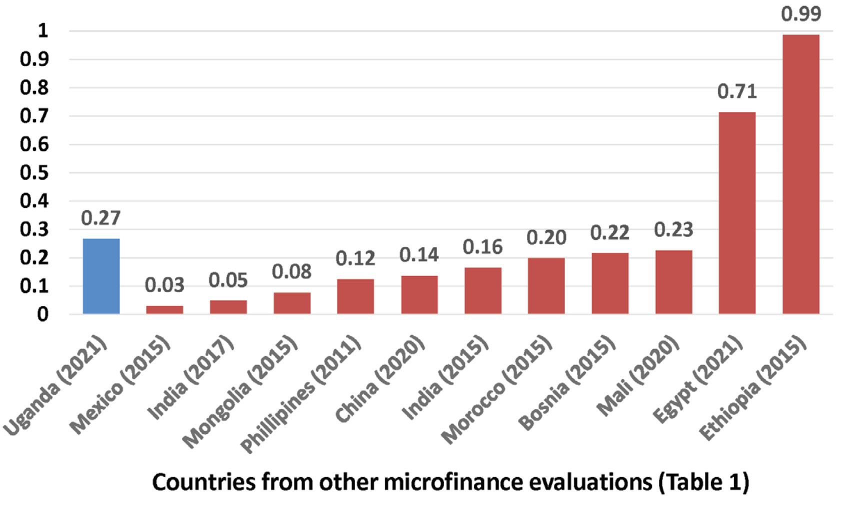

FIGURE 1. Loan size comparisons to other studies (ratio of average loan to GDP per capita).

and 14 others, also evaluated mostly using randomized control trials (RCTs). These include the 'first-generation' RCTs before and including those discussed in Banerjee *et al.* (2015a) as well as a new group of evaluations from the last five years. Panel A describes each study context and baseline access to formal credit in each setting.

In panel B of Table 1, we see overlap in the targeting of women micro-entrepreneurs and other eligibility criteria (such as minimum and maximum ages). In panel C we see considerable overlap in other design features such as the use of group liability, high repayment frequencies, and inflexibly timed repayment structures. Some of these other interventions also require potential borrowers to formulate enterprise plans.

At the same time, the BRAC model differs in several important ways. First, as shown in panel C of Table 1 and Figure 1, loan sizes as a share of GDP per capita are high. Only those considered in Tarozzi *et al.* (2015) in Ethiopia, and Bryan *et al.* (2021) in Egypt, are higher. Moreover, our context is one in which household incomes are low relative to GDP per capita, so our sample is especially drawn from poorer households. This offers another potential reason to expect the BRAC microloans that we evaluate to have the potential to enable borrowing households to overcome any fixed costs of starting a new business and thus diversify their economic activities.[4]

Second, loan officers monitor repayment performance and how loans are utilized and business investment increases. This might be important because close *ex post* monitoring makes the microcredit product more akin to forms of asset based microfinance and graduation programmes, which have been documented to have larger impacts on economic outcomes than is found typically for microcredit interventions (Jack *et al.* 2016; Bandiera *et al.* 2017; Bari *et al.* 2021).

Third, in this setting where the focus in on finding non-agricultural businesses that can generate weekly repayments, women who have such prior experience are more likely to be selected in by BRAC groups. This might be important because microfinance has been documented to have larger impacts on women with prior business experience than those without businesses at baseline (Meager 2020).

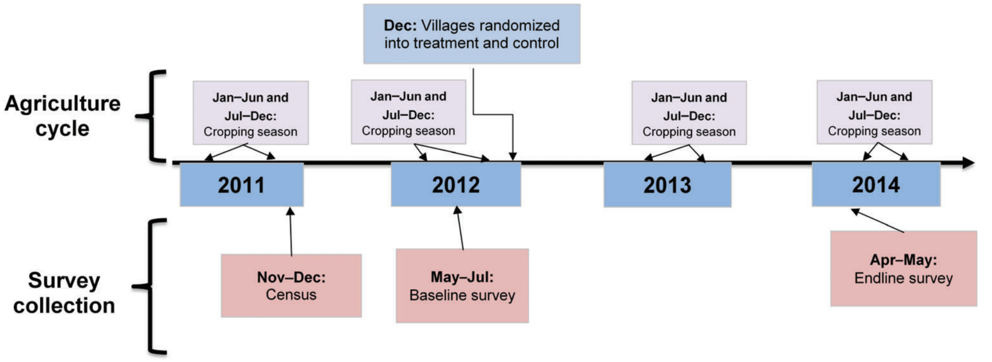

FIGURE 2. Study timeline.

Design

This study is part of a wider project on the determinants of household welfare and economic development in rural Uganda. As part of the project, we evaluated two interventions across villages in rural Uganda, agricultural extension services and the provision of microfinance, using a 2×2 factorial design. The interventions are implemented entirely independently of each other. Microfinance is delivered by centrally located BRAC loan officers (while the agricultural extension programme is implemented by locally recruited delivery agents in adjacent pairs of villages). For the purposes of this study, we do not utilize treatment arms involving the agricultural extension services. That intervention has been evaluated separately (Bandiera *et al.* 2021). Our current evaluation sample thus uses two of the four cells in the 2×2 factorial design. Random assignment takes place at the village level: 59 villages are randomly assigned as controls, and 62 villages are assigned the BRAC microcredit product.

Timeline Figure 2 shows the study timeline, indicating the agricultural cycle and timing of survey waves. We first conducted a census listing in all 121 villages in November/December 2011. Focusing on households where women were eligible to be part of a BRAC credit group, a sample of 4092 households was drawn for our baseline survey fielded from May to July 2012 (corresponding to around 15% of households in each village). 2076 households reside in treated villages, and 2016 reside in controls. We interview female heads of the household. The endline survey takes place two years later, between April and May 2014. There are two six-month cropping cycles per year in this region, and our baseline and endline surveys are timed to take place close to the end of the first cycle in each year.

Our research design and data collection are in line with the approach of earlier studies using village-level randomization, and collecting a sample of borrower and non-borrower households. For example, panel D of Table 1 highlights that most studies use clustered RCTs (the exception being Augsburg *et al.* (2015), which exploits individual-level randomization among marginal loan applicants), and the majority track a panel of households over time.

Balance Table 2 shows village characteristics. Villages are small, with around 215 households in each, thus magnifying any possible spillovers from borrowers to non-borrowers. On a continuous 0–100 household wealth score (constructed from ten underlying indicators, where 100 represents the highest possible level of wealth in this context), the average household wealth index in villages is 54.

TABLE 2
BALANCE ON VILLAGE CHARACTERISTICS

	Control (1)	Treated (2)	p-value (3)
Number of villages	59	62	
Number of households	219.0	214.6	[0.885]
	(73.86)	(93.23)	
Average household wealth score (0–100)	53.51	54.82	[0.178]
	(4.095)	(5.482)	
Number of BRAC microfinance groups	—	1.097	—
		(1.238)	
Distance to nearest control/treated village (km)	1.139	1.114	[0.817]
	(0.614)	(0.602)	

Notes
Standard deviations are shown in parentheses.
Village-level summary statistics for control villages (column (1)) and treated villages (column (2)). The p-values (in square brackets) are obtained from regressing each of the reported baseline variables on the dummy for treatment with robust standard errors and controlling for branch fixed effects. Shortest distance to a control/treated village (miles) is the distance from the control village to the closest treated village in column (1), and the distance from the treated village to the closest control village in column (2). The household wealth score is measured for all households in our baseline survey by aggregating ten poverty indicators into a score from 0 to 100. Average household wealth score (0–100) calculates the average of the wealth score in the village.

In treated villages, the number of BRAC groups established is close to one (each with between 15 and 25 members). The average distance between treatment and control villages is just over 1 km. The two-way (time and monetary) cost of travelling this distance is not prohibitive. It is feasible for women to be willing to travel from control villages in order to participate in BRAC credit groups, conditional on the gains from them so doing being sufficiently large. However, the cumulative costs of weekly travel to group meetings can be more severe and lead to a different selection into microcredit from those in treated and control villages.

Table 3 shows household characteristics; on most dimensions, the samples are well balanced (with any imbalances being relatively small in magnitude). Panel A shows that household heads are aged 42, with low levels of human capital; the majority did not complete primary school, for example. Just under half the households are below the extreme poverty line, so residing on less than the equivalent of \$1.90 per person per day. Hence even among this selected sample of potential micro-entrepreneurial borrowers, there are households residing in extreme economic hardship. Of course, these factors mitigate against the offer of microfinance having transformative effects on the economic lives of eligible women; they might be risk-averse due to residing close to subsistence, and lack the skills necessary to start or expand a business.

Given that microfinance is targeted to women, panel B of Table 3 focuses on labour activities in which women engaged in the year prior to the baseline. As is common in village economies, they engage in multiple labour activities. In the split between agriculture and non-agricultural work, over 85% of women work in agriculture, with around 20% having some form of non-agricultural employment. Among women engaged in some form of work outside of agriculture, 45% are engaged in small-scale trading, and 17% own and run a shop or restaurant. In the split between self-employment and wage employment, again over 85% of women are self-employed (in either agriculture or non-agricultural work). Those designated as self-employed in agriculture are mostly working on their own or rented land. Only 10%

TABLE 3
BALANCE ON HOUSEHOLD CHARACTERISTICS

	Control (1)	Treated (2)	p-value (3)
Number of households	2016	2076	
Panel A: Socioeconomic background			
Number of household members	5.212	5.079	[0.042]
	(2.283)	(2.215)	
Age of household lead	42.41	41.55	[0.288]
	(16.85)	(16.45)	
Household head completed primary education	0.441	0.476	[0.332]
	(0.497)	(0.500)	
In extreme poverty (less than $1.90 per day per person)	0.349	0.293	[0.046]
	(0.477)	(0.455)	
Panel B: Women's labour activities (last year)			
Number of labour activities	1.607	1.533	[0.177]
	(0.833)	(0.826)	
Engaged in agriculture (self-employment or wage activity)	0.879	0.841	[0.195]
	(0.326)	(0.366)	
Engaged in non-agriculture (self-employment or wage activity)	0.196	0.210	[0.742]
	(0.397)	(0.407)	
Engaged in self-employment (agriculture or non-agriculture)	0.885	0.866	[0.526]
	(0.319)	(0.341)	
Engaged in wage labour (agriculture or non-agriculture)	0.121	0.104	[0.521]
	(0.326)	(0.305)	
Panel C: Women's earnings in last year			
Non-agricultural business	243.2	394.4	[0.196]
	(999.4)	(1417)	
Agricultural business	428.2	434.5	[0.835]
	(1141)	(1120)	
Total earnings in last year	482.3	484.8	[0.949]
	(1590)	(1420)	
Panel D: Consumption and savings			
Annual consumption per capita (including home production)	1676	1528	[0.541]
	(10,819)	(8395)	
Annual food consumption per capita (including home production)	949.70	991.28	[0.535]
	(846.6)	(840.6)	
Saved in home	0.564	0.579	[0.516]
	(0.496)	(0.494)	
Saved in banks	0.120	0.156	[0.099]
	(0.325)	(0.363)	
Savings, including zeros	628.4	502.6	[0.926]
	(14,565)	(5962)	
Total assets value	6927	8557	[0.052]
	(10,822)	(14,960)	

Notes
Standard deviations are shown in parentheses.
Household-level summary statistics for control households (column (1)) and treated households (column (2)). The p-values (in square brackets) are obtained from regressing each of the reported baseline variables on the dummy for treatment with robust standard errors and controlling for branch fixed effects. 'Engaged in agriculture' is a dummy variable taking value 1 if the respondent is self-employed in farming, self-employed in animal husbandry or engaged in agricultural wage labour. 'Engaged in non-agriculture' is a dummy variable taking value 1 if the respondent is engaged in non-agricultural self-employment or non-agricultural wage labour. 'Engaged in self-employment' is a dummy variable taking value 1 if the respondent is self-employed in either agriculture or non-agriculture. 'Engaged in wage labour' is a dummy variable taking value 1 if the respondent works for a wage. Earnings in non-agricultural business is the difference between revenues and input costs for respondents who are self-employed in non-agricultural business. Earnings in agricultural business is the difference between revenues and input costs for respondents who are self-employed in agricultural business. Total earnings are the sum of profits from self-employment, profits from agriculture sales, profits from animal husbandry, and wages. Consumption is an annual variable constructed from food consumed in the last 7 days, consumer non-durables purchased in the last month, and consumer durables purchased in the last year. 'Saved in home' and 'Saved in banks' are dummy variables taking value 1 if the respondent reports savings held at home or at a bank, respectively. 'Total assets value' includes the value of all household assets that fall into the categories house, furniture, agricultural assets, business assets, transportation assets. All monetary values are expressed in 2014 USD PPP.

are wage workers, mostly engaged in non-agricultural work. Hence in terms of potential extensive margin impacts of the intervention, a key impact is whether women use credit to help to finance a switch from agricultural work towards some form of non-agricultural employment. On the intensive margin, some borrowers might also use the credit to expand the scale of their current economic activities without changing sector.

In both cases, given frequent repayment rates, they would only be willing to do so if either the new investment financed by the microloan generated an immediate return, or they were willing to run down their stock of savings or reduce consumption in the transition before the returns to investment began to be realized. This is less likely to be the case for labour activities based on agriculture, where earning streams are often bunched at certain times of the year, and are volatile at those times of year, creating demand for short-run liquidity for consumption smoothing (Casaburi and Willis 2018; Casaburi and Macchiavello 2019).

Panel C of Table 3 shows the relative importance of different economic activities in terms of actual earnings generated. Earnings are defined as the difference between revenues and input costs for self-employed respondents, so these can be negative. Total earnings are the sum of earnings from self-employment and wages. Among those engaged in such activities, earnings from non-agricultural work are higher than those from agriculture. Across all income-generating activities, total annual earnings for women are around \$480. Hence the typical loan size taken of \$550 is the equivalent of a one-off injection of 115% of women's annual earnings, which is high in comparison to the figures for the global microfinance industry described in Buera *et al.* (2020).[5]

To get a sense of the average returns to different labour activities, we note that in control villages, monthly hours devoted to agriculture are 94, while those devoted to non-agricultural work are 42. Hence the average hourly return is \$0.18 for agriculture, and more than twice as high at \$0.48 for non-agricultural work. Of course, women self-select into these activities, so these average differentials do not reflect the counterfactual marginal return for new entrants. However, this comparison is consistent with the notion that returns to non-agricultural work are potentially higher than for agricultural work in this context, and at least some women would like to diversify labour activities into non-agricultural work given the opportunity to do so, and so diversify the earning stream of their household overall.

Finally, panel D of Table 3 focuses on consumption and savings. In controls, annual consumption per capita (including the value of home production that mostly relates to own grown food) is \$1100. Food consumption constitutes over 80% of the total value of consumption. The majority of households lack access to formal savings, with most retaining their in-kind and cash savings at home. The total stock of savings in controls is \$628, and total asset holdings are around \$7000.[6]

Attrition Table 4 shows correlates of household attrition from baseline to the two-year endline. Attrition is relatively low (10%), but is weakly correlated to treatment: treated households are 3 percentage points more likely to attrit than controls. However, we find no evidence of differential attrition by characteristics of households in treatment and control villages; the p-value on the joint significance of baseline household characteristics interacted with the treatment dummy is 0.718.

Credit markets

To begin to see how BRAC's entry could shape credit markets in these village economies, we describe pre-intervention: (i) the extent to which households already engage in credit transactions; (ii) the sources of credit available.

TABLE 4
ATTRITION

	No covariates (1)	Covariates (2)	Covariates plus their interaction with treatment (3)
Treated	0.030*	0.029*	0.034
	(0.016)	(0.016)	(0.051)
Household head completed primary education		0.018	0.011
		(0.011)	(0.014)
Wealth score (0–100)		0.001*	0.001**
		(0.001)	(0.000)
Engaged in non-agricultural business		0.026*	0.036*
		(0.016)	(0.020)
Borrowed from informal sources		−0.015	−0.027**
		(0.011)	(0.013)
Total consumption		0.000	−0.000
		(0.000)	(0.000)
Treated × Household head completed primary education			0.013
			(0.023)
Treated × Wealth score (0–100)			−0.000
			(0.001)
Treated × Engaged in non-agricultural business			−0.020
			(0.032)
Treated × Borrowed from informal sources			0.026
			(0.022)
Treated × Total consumption			0.008
			(0.007)
Mean dependent variable	0.098	0.098	0.098
p-value on interactions	—	—	[0.718]
Observations	4092	3951	3951

Notes
Standard errors are clustered at the village level and shown in parentheses; p-value in square brackets.
OLS estimates are reported based on the sample of households observed at baseline. The dependent variable is a dummy taking value 1 if the household is observed in both the baseline and the follow-up survey; otherwise it is 0. All specifications control for branch-level fixed effects.
***, **, * indicate significance at the 1%, 5%, 10% level, respectively.

Table 5 shows evidence on household engagement in credit markets. Panel A shows sources of borrowing, split between informal and formal sources. Informal borrowing is far more prevalent, as expected: 24% of households report having borrowed from some informal source. Households are as likely to borrow from family/friends as they are to borrow from local savings cooperatives. In contrast, 5% of households report ever having borrowed from some formal source—including from another MFI or NGO. Panel B shows that there is a small share of households that lend to others: credit is provided mostly to friends (13%), followed by family members (7%).

Along all dimensions of engagement in credit transactions, treatment and control households are well balanced. Table 6 details various sources of credit in our setting, split between semi-formal, informal and formal sources. For each source, we use baseline data, except for the BRAC microloan product—where we use endline reports to characterize its product features. Given loan cycles are shorter than our two-year study period between baseline and endline; by endline, around three-quarters of borrowers are on their first or

TABLE 5
ENGAGEMENT IN CREDIT TRANSACTIONS

	Control (1)	Treated (2)	p-value ((1) = (2)) (3)
Number of households	2016	2076	
Panel A: Borrowing			
Borrowed from informal sources	0.242	0.217	[0.456]
	(0.429)	(0.412)	
Borrowed from family or friends	0.231	0.206	[0.427]
	(0.422)	(0.405)	
Borrowed from local savings/cooperatives	0.222	0.226	[0.967]
	(0.416)	(0.418)	
Borrowed from formal sources	0.048	0.055	[0.603]
	(0.214)	(0.123)	
Borrowed from MFI	0.014	0.020	[0.272]
	(0.117)	(0.139)	
Borrowed from NGOs	0.002	0.002	[0.678]
	(0.045)	(0.049)	
Panel B: Lending			
Lend to family	0.068	0.060	[0.462]
	(0.251)	(0.237)	
Lend to friends	0.137	0.129	[0.648]
	(0.344)	(0.335)	
Lend to other people	0.003	0.006	[0.151]
	(0.055)	(0.076)	

Notes
Standard deviations are shown in parentheses.
Household-level summary statistics for control households (column (1)) and treated households (column (2)). The p-values (in square brackets) are obtained from regressing each of the reported baseline variables on the dummy for treatment with robust standard errors and controlling for branch fixed effects. Each variable in panels A and B is a dummy taking value 1 if the respondent reports having borrowed or lent from/to each source. Borrowing from formal sources incudes MFIs, NGOs and banks.

second loan cycle. The figures reported relate to their last loan from BRAC. At endline, the cumulative amount borrowed from BRAC amounts to just over $1000 for the average borrower.

The following key features of the BRAC product stand out relative to other credit sources available in this setting.

The BRAC microloan enables households to borrow far larger amounts than provided by other lenders (even formal ones from whom households obtain loans); 5.4% of households in our sample report borrowing from BRAC at endline (from across treated and control villages), and the average amount borrowed is $555. The next largest amounts borrowed are from other microfinance organizations ($505, but from whom less than 0.6% of households report having borrowed), formal banks ($359, 0.8%) and private moneylenders ($216, 1.5%). Amounts borrowed from friends and family are on average less than $100.

The amount available from the new BRAC product corresponds to 115% of the total annual earnings of women, six times the value of total monthly per capita consumption, or 88% of the stock of household savings at baseline. Moreover, there is wide variation in the amounts borrowed. Figure 3 shows the entire distribution of amounts borrowed from BRAC,

TABLE 6
SOURCES OF CREDIT

	Have you ever obtained a loan from …?	Is there a … that lends money in your village?	How much did you borrow (2014 USD PPP)?	If you were to borrow now 250,000 Ugandan shillings (232.84 USD) from … (based on the answer to 'Is there a … that lends money in your village?')				Implied monthly interest rate	Implied annual interest rate
				Would the loan require any security?	Would the repayment date be flexible?	How many months later would you have to repay the loan?	How much would you have to pay back in total (2014 USD)?		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Semi-formal									
BRAC (endline survey data)	0.054		554.93	Not required	0.000	9.748	289.7	2.27%	30.86%
	(0.226)		(231.6)			(3.219)	(20.06)		
MFI	0.006	0.026	505.44	0.778	0.390	8.789	256.2	1.09%	13.90%
	(0.078)	(0.159)	(602.4)	(0.420)	(0.492)	(6.115)	(46.59)		
Cooperative	0.034	0.082	163.15	0.604	0.601	6.625	248.1	0.96%	12.19%
	(0.181)	(0.274)	(321.63)	(0.490)	(0.491)	(5.047)	(43.01)		
Village-level assoc. (SACCOS)	0.211	0.392	168.10	0.551	0.672	5.828	276.4	2.99%	42.35%
	(0.408)	(0.488)	(268.3)	(0.498)	(0.470)	(4.624)	(87.25)		
Panel B: Informal									
Relatives/family	0.266		98.54	0.150	0.808	6.542	237.9	0.33%	4.02%
	(0.442)		(151.93)	(0.357)	(0.394)	(5.946)	(51.92)		
Friends	0.304		91.56	0.188	0.781	6.330	243.9	0.74%	9.20%
	(0.460)		(198.90)	(0.391)	(0.414)	(7.008)	(58.44)		
Private money lender	0.015	0.080	216.17	0.652	0.553	5.468	310.6	5.41%	88.20%
	(0.122)	(0.271)	(449.29)	(0.478)	(0.499)	(3.889)	(98.1)		
Other	0.072	0.147	73.65	0.401	0.749	6.448	299.2	3.97%	59.47%
	(0.258)	(0.355)	(99.01)	(0.491)	(0.434)	(6.493)	(89.27)		
Panel C: Formal									
Bank (commercial/development)	0.008	0.032	358.78	0.743	0.611	4.231	239.7	0.69%	8.58%
	(0.090)	(0.175)	(564.8)	(0.440)	(0.491)	(2.421)	(76.13)		
Other	0.016	0.026	31.56	0.351	0.798	8.909	300.1	2.89%	40.75%
	(0.127)	(0.160)	(42.43)	(0.480)	(0.404)	(13.39)	(195.0)		

Notes
Standard deviations are shown in parentheses.
Household-level summary statistics for access to credit markets at baseline. The BRAC row is imputed from endline data on the actual borrowing of respondents. Data on non-BRAC credit sources were collected in the baseline survey. The questions 'Have you ever obtained a loan from …?' and 'Is there a … that lends in your village?' are asked of all respondents and averaged over the whole sample. Column (3) ('How much did you borrow?') summarizes the loan amounts among borrowers. Columns (4)–(7) summarize the loan conditions among respondents who reported borrowing from each source. In column (8), the implied monthly interest rate is calculated using $A = P(1 + r)t$, where A is the amount owed, P is the initial loan principle, r is the monthly interest rate, and t is the repayment period in months. All monetary values are expressed in 2014 USD PPP.

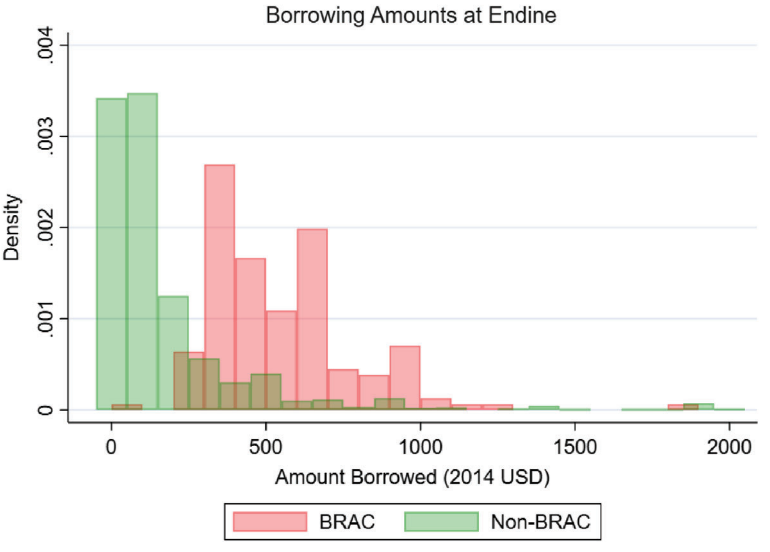

FIGURE 3. Loan sizes from BRAC and other sources. *Notes*: Histogram of amounts borrowed from BRAC and non-BRAC in 2014 USD at endline survey, among those with non-zero borrowing. Rightmost bin includes upper tail of borrowers (over 2000 USD). 1073.7 UGX = 1 USD in purchasing power parity.

and those for other major sources of credit. The two distributions have little common support. The amounts borrowed from BRAC range from \$200 to over \$1500.

BRAC loans do not require security; group-based liability essentially takes the place of such requirements. On the other hand, repayment schedules are entirely inflexible with BRAC microloans, and the implied monthly interest rate reported by households is, at 2.27%, higher than rates charged by a number of other sources. Unsurprisingly, private moneylenders charge the highest interest rate (5.41%). The extent to which these differences in monthly interest rates accumulate to differential annual interest rates is shown in column (9) of Table 6.[7]

Three points are of note.

First, multiple credit sources can coexist if households vary in their demand for credit in terms of the amounts demanded, flexibility of repayments, and so on. Microfinance—with its inflexible repayment structures—is not well suited to those engaged in agriculture, given that earnings streams tend to be volatile and bunched at certain times of the year, hence the focus of BRAC and other MFIs on credit provision targeting micro-entrepreneurship.[8]

Second, the entry of BRAC into these credit markets represents households having access to microcredit for the first time as less than 1% have borrowed from an MFI before. However, the BRAC product remains one of a large number of credit sources available. To the extent that BRAC microcredit simply causes households to substitute away from pre-existing credit sources that offer similar terms, this reduces the net economic impacts of BRAC microloans between treated and control villages.

Third, comparing product characteristics suggests that we should expect non-random selection into BRAC microfinance groups and the take-up of loans. Those who borrow from BRAC rather than other sources might be selected positively in that they demand more credit but are willing to take on such loans despite the inflexible timing of repayment and higher interest rates.

Estimation

Our empirical analysis proceeds as follows. First, we examine the correlates of women's take-up with the offer of credit from BRAC, namely whether they join a BRAC microfinance group and borrow from this source. Given that women in treated and control locations can potentially join groups, the nature of selection into microloans might differ between those in treated and control villages. We explore heterogeneous effects of characteristics on compliance using the specification

$$BRAC\_Borrower_{iv} = \alpha + \tau_0 T_v + \tau_1 (T_v \times X_{i0}) + \tau_2 X_{i0} + \lambda_s + u_{iv}, \tag{1}$$

where $BRAC\_Borrower_{iv}$ is a dummy equal to 1 if woman i from village v reports having borrowed from BRAC at endline, T_v is a dummy measuring the treatment assignment of village v, and X_{i0} is the characteristic considered for the heterogeneous analysis (measured at baseline). We include village-level randomization strata, λ_s, that are dummies for BRAC branch, village size, the share of households primarily engaged in farming, and distance to the local market.

Second, we measure intent-to-treat (ITT) impacts two years post-intervention using the following ANCOVA specification for household i in village v:

$$y_{iv1} = \alpha + \beta^{\text{ITT}}\, T_v + \gamma\, y_{iv0} + \lambda_s + u_{iv}, \tag{2}$$

where y_{iv1} is the outcome of interest at endline ($t = 1$), and y_{iv0} is the outcome of interest at baseline ($t = 0$). We allow standard errors to be clustered by village, and report Westfall–Young p-value corrections for multiple hypothesis testing (Young 2019).

The statistical power to detect treatment effects hinges critically on the degree of differential take-up between treatment and control villages. In common with some other microfinance studies, we find relatively low take-up in treated villages, and we observe a non-trivial (lower) level of compliance in control villages. This reflects the fact that microfinance is targeted towards those with micro-entrepreneurial intent (so not *all* households are targeted), and there are often multiple pre-existing credit sources available to households in village economies.

Third, for completeness and to try to shed light on impacts among those that select into borrowing from BRAC, we estimate the following treatment-on-the-treated (TOT) specification:

$$y_{iv1} = \alpha + \beta^{\text{TOT}}\, BRAC\_Borrower_{iv} + \gamma\, y_{iv0} + \lambda_s + u_{iv}, \tag{3}$$

where we instrument $BRAC\_Borrower_{iv}$ using the offer of treatment (the village treatment dummy T_v). Spillovers to control villages weaken the instrument, so these estimates should be treated with caution. Moreover, the effective scaling-up of ITT estimates into TOT estimates requires the strong additional assumption that there are no spillover effects of the offer of microfinance. These could occur plausibly within villages through multiple channels, such as the expectation of future credit access, business creation, higher labour demand, reduced precautionary savings, changes in informal lending or risk-sharing arrangements (Kaboski and Townsend 2011; Banerjee *et al.* 2015b; Meager 2020; Breza and Kinnan 2021). Furthermore, there are likely concerns with treatment heterogeneity, wherein those who take up loans have higher returns to capital than those who do not (Beaman *et al.* 2020; Crépon *et al.* 2020; Meager 2020; Bryan *et al.* 2021).

Together, these factors mean that we place relatively more focus on the ITT results; but we present both sets of estimates throughout.

At a final stage, we reflect on the fact that there is huge variation in the amounts borrowed from BRAC—as shown in Figure 3. Hence the intensity of treatment from the availability of microfinance varies across borrowers. We use the following specification to estimate the intensity effect of treatment:

$$y_{iv1} = \alpha + \beta^{\varepsilon}\ BRAC\_Amount_{iv} + \gamma\ y_{iv0} + \lambda_s + u_{iv}, \tag{4}$$

where $BRAC\_Amount_{iv}$ is the size of the last loan that woman i takes from BRAC. We again instrument loan size with the village treatment dummy T_v. We focus on estimates where outcomes y_{iv1} are in logs and in monetary amounts, so β^{ε} captures the elasticity of the monetary outcome with regards to BRAC loans.

II. Results

Take-up

Table 7 shows estimates from equation (1). To begin with, we control only for the village treatment assignment dummy. Column (1) shows that take-up is 3.2 percentage points higher among women in treated villages than in controls. At the foot of the table, we report the take-up rate in controls: this is 3.4%, so just over half the overall take-up rate in treated villages. Three points are of note.

First, take-up is low—this is as expected given that only a small share of households could possibly comply and borrow from BRAC across treated villages. As BRAC groups are fixed to have between 15 and 25 members, most treated villages establish one group, and average village size is around 215 households. Hence with one group, the highest plausible take-up rate within treated villages is 12%.

Second, there are across-village spillovers of the microloan programme in the sense that some share of individuals in controls are willing to travel to treated villages in order to join a BRAC group. Hence there might be differential selection on gains into joining BRAC groups between those in treated and control villages.

Third, in comparison to the studies summarized in Banerjee *et al.* (2015a) and Table 1, take-up rates in our study are among the lowest—this might go hand in hand with the fact that loan sizes are far larger than from other credit sources in these village economies. Only those with sufficiently high return to large investment would borrow from BRAC—smaller amounts are available from other credit sources in these villages. The primary determinant of statistical power—the difference in take-up between treated and control subjects—is also lower than other studies, at 3.2%. However, that households in control villages also appear to take up the offer of credit is a phenomenon not restricted to our study context—other microfinance studies also find high take-up rates in controls, and in some cases take-up rates in controls are also more than half those in actual treated villages.

The remaining columns in Table 7 examine heterogeneous take-up. At the foot of each column, we report the levels coefficient on the interaction, interpreted as how the interacted characteristic correlates to take-up among women in control villages.

Column (2) of Table 7 shows that women who have borrowed from any source in the last year are more likely to borrow from BRAC. This applies to those in both control and treated villages, although those in treated villages are even more likely to do so (the difference is significant at the 10% level). This reinforces the notion of differential selection into borrowing from BRAC across treated and control women. It also suggests that women's access to credit across sources is positively correlated over time. We come back to this point below, when examining whether borrowing from BRAC complements or substitutes for other sources of

TABLE 7
TAKE-UP

	Baseline	Credit market	Labour activities		Earnings and wealth		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment [1]	0.032***	0.019*	0.026**	0.034***	0.034***	0.026**	0.034***
	(0.011)	(0.010)	(0.012)	(0.010)	(0.011)	(0.010)	(0.011)
Treatment [1] × Borrowed money in last year		0.027*					
		(0.016)					
Treatment [1] × Self-employed			0.008				
			(0.016)				
Treatment [1] × Engaged in non-agricultural labour				−0.010			
				(0.018)			
Treatment [1] × Earnings					−0.000		
					(0.000)		
Treatment [1] × Above 90th percentile baseline earnings						0.060***	
						(0.022)	
Treatment [1] × Above 90th percentile baseline wealth							−0.007
							(0.016)
Level coefficient	0.020**		0.030***	0.044***	0.000	−0.009	−0.014
		(0.008)	(0.007)	(0.011)	(0.000)	(0.011)	(0.012)
Mean in controls	3.4%	3.4%	3.4%	3.4%	3.4%	3.4%	3.4%
F-statistic	9.32						
Stratification controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Omitted group			Wage	Agriculture			
Adjusted R-squared	0.015	0.021	0.016	0.019	0.015	0.017	0.015
Observations	4092	4092	4092	4092	4092	4092	4092

Notes
Standard errors clustered by village in parentheses. Dependent variable: Take-up (BRAC borrower at endline).
All regressions control for branch fixed effects and stratification variables. Treatment is a dummy variable taking value 1 if the respondent lives in a village that received the microfinance treatment. 'Borrowed money in last year' is a dummy variable taking value 1 if the respondent reported receiving any loans at baseline. 'Engaged in non-agricultural labour' is a dummy variable taking value 1 if the respondent is engaged in non-agricultural self-employment or non-agricultural wage labour at baseline. Earnings is the sum of profits from self-employment, profits from agriculture sales, profits from animal husbandry and wages. The household wealth score is measured for all households in our baseline survey by aggregating ten poverty indicators into a score from 0 to 100. 'Mean in controls' reports the average microfinance take-up rate across all villages at baseline. All monetary values are expressed in 2014 USD PPP.
***, **, * indicate significance at the 1%, 5%, 10% level, respectively.

credit. The result also highlights another caveat to most microfinance studies, including this one, that target micro-entrepreneurs: that we can say less on the impacts of new credit sources on inframarginal borrowers, rather than those with access to credit pre-intervention.[9]

Columns (3) and (4) of Table 7 examine heterogeneous take-up by the type of labour activity engaged in by women at baseline. We see a positive association with engagement in self-employment (relative to wage employment), and for those engaged in non-agricultural work (relative to agricultural work). The effect does not differ between borrowers from treated and control villages, but both are in line with the credit being targeted towards micro-entrepreneurs as intended.

Given the differential characteristics of credit sources emphasized earlier, columns (5)–(7) of Table 7 focus on how baseline measures of respondent earnings and household wealth correlate with take-up. None of these predict take-up among controls, while in treated villages, women at or above the 90th percentile of the earnings distribution are significantly more likely to become BRAC borrowers by endline. However, this does not apply to those in controls. This is consistent with higher-earning women having easier access to credit from other sources in both treatment and control villages, and therefore among those in controls, choosing not to incur the recurrent travel costs to treatment villages to attend weekly group meetings.

Across the columns of Table 7, we note the very low adjusted R-squared, highlighting the difficulty in predicting compliance based on observables. This is true within both the microfinance literature and studies using information on enterprise business plans (as formulated by potential BRAC borrowers) to predict future success (McKenzie 2015, 2018; Fafchamps and Woodruff 2017; McKenzie and Sansone 2019). An important and promising avenue of current research investigates further what drives the selection into microfinance and whether potential gains from take-up are known privately to individuals, identifiable by community members or recoverable to the econometrician using machine learning approaches (Beaman *et al.* 2020; Bryan *et al.* 2021; Hussam *et al.* 2021).[10]

Labour activities

We first consider labour market activities of women. Given the nature of constraints on agricultural productivity in this context, enabling households to diversify economic activities and generate earnings streams from work in non-agricultural jobs seems a key intermediate step for microfinance to have any impact on economic welfare.

Panels A and B of Table 8 show ITT and TOT estimates using specifications (2) and (3). For the latter, the relevant first stage is in column (1) of Table 7, with F-statistic 9.3. The instrument is weak due to the across-village spillovers documented above.

Given the dominance of self-employment activities in our context, columns (1) and (2) of Table 8 focus on agricultural and non-agricultural work. The ITT estimates show a shift on the extensive margin of women out of agriculture and into non-agriculture. The magnitudes of impacts are large: the 3.1 percentage points reduction in agriculture corresponds to 3.7% reduction over the baseline mean in controls, and the 6.1 percentage points increase into non-agriculture corresponds to a 47% increase over the baseline mean in controls. The pattern of results is robust to p-value corrections for multiple hypothesis testing.

Subject to the caveats described earlier, the TOT estimates in panel B of Table 8 remain precise for the shifts into self-employed non-agricultural work. Indeed, we cannot reject $\widehat{\beta}^{\mathrm{TOT}} = 1$ on this margin, so that *all* BRAC borrowers make this transition into non-agricultural labour activities. This is in line with the intent of the programme: to foster micro-entrepreneurship among eligible women.

TABLE 8
LABOUR ACTIVITIES AND DIVERSIFICATION

	Labour activities		Labour supply		Agricultural outcomes			Non-agricultural outcomes	
	Engaged in agriculture	Engaged in non-agricultural self-employment	Monthly hours in agriculture	Monthly hours in non-agriculture	Acres of land cultivated	Share of output sold	Number of crops grown	Small trade	Shop owner etc.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: ITT village treatment									
Treatment village = 1	−0.031*	0.061***	−8.70*	10.83**	−0.016	0.026	−0.138	0.028**	0.008
	(0.018)	(0.022)	(4.66)	(5.23)	(0.068)	(0.018)	(0.118)	(0.013)	(0.009)
	{0.094}	{0.008}	{0.076}	{0.076}	{0.830}	{0.388}	{0.434}	{0.052}	{0.390}
Panel B: TOT estimates (IV = village treatment assignment)									
BRAC borrower	−0.797	1.69**	−307	304*	−0.416	0.624	−3.63	0.873*	0.241
	(0.524)	(0.777)	(205)	(173)	(1.69)	(0.476)	(3.31)	(0.453)	(0.281)
	{0.104}	{0.680}	{0.142}	{0.142}	{0.829}	{0.376}	{0.406}	{0.094}	{0.358}
Control mean at baseline	0.832	0.129	93.7	41.7	0.934	0.411	2.50	0.114	0.035
Control mean at baseline (non-zero)			112	172	1.10	0.411	2.96		
Baseline level included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3692	3692	3464	3692	3680	3128	3692	4092	4092

Notes
Standard errors clustered by village in parentheses. Westfall–Young p-values for multiple hypothesis testing are shown in braces.
Panel A shows ITT results regressing the variable of interest on a dummy variable for whether the respondent lives in a treatment village, the baseline level of the dependent variable, and a constant. Groups for multiple hypothesis testing are those in columns (1)–(2), (3)–(4), (5)–(7) and (8)–(9). Panel B shows the TOT results by running 2SLS with a dummy taking value 1 if the respondent lives in a treatment village as an instrument for borrowing from BRAC at follow-up. We control for the level of the outcome variable at baseline and randomization strata. 'Engaged in agriculture' is a dummy variable taking value 1 if the respondent is engaged in agriculture or animal husbandry. 'Engaged in non-agricultural self-employment' is a dummy variable taking value 1 if the respondent is engaged in non-agricultural self-employment. Monthly hours worked variables are the number of hours worked in a typical day multiplied by the number of days worked: in the last year divided by 12 for non-agricultural work, and in the last season divided by 6 for agricultural work. 'Small trade' and 'Shop owner' are dummy variables taking value 1 if the respondent reports either field as their primary occupation.
***, **, * indicate significance at the 1%, 5%, 10% level, respectively.

We next consider the intensive margin of monthly hours of labour supply in each activity. The same pattern of impact is found as on the extensive margin. The ITT estimates imply a significant reduction in labour supply in agriculture, and significant increases in labour supply in non-agricultural work, but both results are estimated imprecisely in the TOT impacts for actual borrowers (panel B, columns (3) and (4) of Table 8). The ITT estimate shows that the monthly labour supply reduction in agriculture is almost the same magnitude as the increase in non-agricultural activities. At the same time, the estimates show that while women use BRAC credit to diversify or scale up activities in non-agricultural work, they do not do so at the expense of giving up on agricultural work altogether. This in line with findings from large-scale asset transfer interventions (Bandiera *et al.* 2017), where it is found that over a similar two-year time horizon, asset transfers lead to a reallocation of labour activities from agriculture to non-agricultural work. It is only over the longer term that such asset transfer evaluations find that the poor are also willing to supply more labour overall if given productive opportunities to do so.

In columns (5)–(7) of Table 8, when we examine in more detail impacts across outcomes specific to agriculture, the ITT estimates suggest no significant shifts down in the scale of agricultural production in terms of the number of crops grown, or the share of output that is sold (rather than consumed). This reaffirms the notion that—at least over the two-year horizon of our evaluation—households diversify economic activities, rather than altogether switching economic activities, or using the newly available source of credit to scale up expansion into existing non-agricultural businesses.[11]

Finally, columns (8) and (9) of Table 8 focus on the two most prevalent forms of non-agricultural work at baseline: small trade and shop ownership. The ITT and TOT estimates both imply that women are significantly more likely to start engaging in some small trade form of micro-entrepreneurship. Indeed, the TOT estimate in panel B implies that the majority of borrowers expand activities on the extensive margin to set up in some small-scale trade ($\widehat{\beta}^{\mathrm{TOT}} = 0.873$), a finding robust to multiple hypothesis testing.

Individual earnings

We next build on the patterns of economic diversification into non-agricultural labour activities to shed light on earnings impacts on women. For these results, we have the important caveat that there could be severe measurement error in any monetary outcome (Karlan and Zinman 2012). In Table 9, we see that in line with much of the earlier literature, the ITT estimates on aggregates related to earnings are positive but very imprecise, hence we cannot rule out a very wide range of estimates (Banerjee *et al.* 2015a). The low rate of take-up means that we lack power to detect effects at the right tail of the earnings distribution, yet that tail is likely to have disproportionate influence for village-wide outcomes (Meager 2020).

In columns (4) and (5) of Table 9, we use cruder indicators of whether positive earnings are generated from each labour activity. We see some evidence of a higher likelihood of positive earnings being generated from non-agricultural work, the magnitude of the ITT impact being 3.4 percentage points. We also find that earnings from agriculture are more likely to be non-positive—this might reflect the relative low scale of production of such remaining activities given the switches on the extensive margin, or also capture some women moving out of agricultural work altogether.

The TOT estimates in panel B of Table 9 give a very similar pattern of results—with estimates being estimated imprecisely, and not ruling out large potential increases. The fact that TOT earnings impacts remain imprecise even for non-agricultural labour activities might also be due partly to the concentration of women in non-agricultural activities in just a few

TABLE 9
INDIVIDUAL EARNINGS

	Total earnings (1)	Earnings from agricultural labour (2)	Earnings from non-agricultural labour (3)	Earnings from agricultural labour > 0 (4)	Earnings from non-agricultural labour > 0 (5)
Panel A: ITT village treatment					
Treatment village = 1	7.42	−9.38	14.9	−0.050**	0.034*
	(67.7)	(60.8)	(26.9)	(0.021)	(0.018)
	{0.958}	{0.958}	{0.840}	{0.034}	{0.074}
Panel B: TOT estimates (IV = village treatment assignment)					
BRAC borrower	197	−249	400	−1.58*	1.05
	(178)	(1630)	(737)	(0.911)	(0.656)
	{0.968}	{0.968}	{0.844}	{0.184}	{0.184}
Control mean at baseline	482	371	112	0.667	0.133
Control mean (conditional on participation)		428	695		
Baseline level included	Yes	Yes	Yes	Yes	Yes
Observations	3692	3692	3692	4092	4092

Notes
Standard errors are clustered at the village level and shown in parentheses. Westfall–Young p-values for multiple hypothesis testing are shown in braces.
Panel A shows ITT results regressing the variable of interest on a dummy variable for whether the respondent lives in a treatment village, the baseline level of the dependent variable and a constant. Groups for multiple hypothesis testing are those in columns (1)–(3) and (4)–(5). Panel B shows the TOT results by running 2SLS with a dummy taking value 1 if the respondent lives in a treatment village as an instrument for borrowing from BRAC at follow-up. We control for the level of the outcome variable at baseline and randomization strata. Earnings from (non-)agriculture are the sum of profits from self-employment in (non-)agriculture plus any earnings from wage labour in (non-)agriculture. All monetary values are expressed in 2014 USD PPP.
***, **, * indicate significance at the 1%, 5%, 10% level, respectively.

types of work; recall that at baseline, among women engaged in some form of work outside of agriculture, 45% are engaged in small-scale trading, and 17% own and run a shop or restaurant.

Credit

We next examine impacts on engagement in credit markets—specifically, the ability to borrow from non-BRAC sources as well as lend to others. The entry of BRAC into these rural credit markets provides women with an additional source of credit (rather than accessing microfinance for the first time). In terms of deepening engagement in credit markets, it is thus important to understand whether BRAC credit complements or substitutes for other credit sources.

In panel A of Table 10, we see that the ITT impacts are imprecise (as are the TOT estimates reported in panel B). BRAC microloans thus appear to be neither complements nor substitutes for other credit sources. This implies that perhaps households are no longer credit-constrained after having access to BRAC microloans, consistent with the scale of loans being far larger than available from other sources. Reassuringly, the result is also consistent with households not entering debt traps because they need to engage in further borrowing in order to pay off existing loans.

TABLE 10
CREDIT MARKETS

	Borrowed from any non-BRAC source in last year (1)	Borrowed from any non-BRAC formal source in last year (2)	Borrowed from any informal source in last year (3)	Lent to family and friends (4)
Panel A: ITT village treatment				
Treatment village = 1	0.000	0.002	0.013	0.029
	(0.025)	(0.005)	(0.022)	(0.019)
	{0.986}	{0.922}	{0.882}	{0.418}
Panel B: TOT estimates (IV = village treatment assignment)				
BRAC borrower	0.013	0.054	0.356	0.765
	(0.766)	(0.140)	(0.579)	(0.576)
	{0.990}	{0.922}	{0.870}	{0.446}
Control mean at baseline	0.514	0.048	0.242	0.202
Baseline levels included	Yes	Yes	Yes	Yes
Observations	3692	4092	3655	3692

Notes
Standard errors are clustered at the village level and shown in parentheses. Westfall–Young p-values for multiple hypothesis testing are shown in braces.
Panel A shows ITT results regressing the variable of interest on a dummy variable for whether the respondent lives in a treatment village, the baseline level of the dependent variable and a constant. We group all variables in this table for the multiple hypothesis testing. Panel B shows the TOT results by running 2SLS with a dummy taking value 1 if the respondent lives in a treatment village as an instrument for borrowing from BRAC at follow-up. We control for the level of the outcome variable at baseline and randomization strata. Credit market variables are a dummy taking value 1 if the respondent reports having borrowed from any of the sources.
***, **, * indicate significance at the 1%, 5%, 10% level, respectively.

Consumption, savings, assets and wealth

Our final set of outcomes considers how the patterns of economic diversification into non-agricultural labour activities translate into economic aggregates related to consumption, savings, asset accumulation and welfare. As for earnings, we have the caveat that there is likely to be measurement error in these monetary outcomes, so it is not straightforward to trace how credit is utilized (Karlan and Zinman 2012). As Banerjee *et al.* (2015b) describe, improved credit access can affect consumption and/or investment. For example, credit allows households to make lumpy consumption purchases (say on durables), or it might allow for more investment without cutting back consumption, and for higher consumption today at the cost of lowered future consumption.

To begin examining such impacts, column (1) of Table 11 focuses on the value of consumption (including home-produced food). Panel A shows null ITT impacts for consumption, and the same is found in the TOT estimate in panel B for actual BRAC borrowers (although the point estimate is positive). Columns (2)–(5) break down types of consumption expenditure. We see that there are very large (but imprecise) increases in the value of food consumption, while there are no precise impacts on discretionary spending, spending on durables, or spending on health or education.[12]

We can also begin to explore the possibility that microfinance can improve consumption smoothing, even if it does change the level of consumption (Morduch 1998). We do not have enough rounds of data collection to construct a measure of consumption smoothing within a household over time, but we can assess indirectly the possibility by estimating impacts on the

TABLE 11
CONSUMPTION, SAVINGS, ASSETS AND WEALTH

	Consumption, p.c.e. (log) (1)	Value of food (including home production), p.c.e. (log) (2)	Discretionary spending, p.c.e. (log) (3)	Spending on health and education, p.c.e. (log) (4)	Spending on durables, p.c.e. (log) (5)	Savings (log) (6)	Total assets (log) (7)	Wealth score (8)
Panel A: ITT village treatment								
Treatment village = 1	0.046	0.086	0.085	0.056	0.097	0.203	0.002	−1.08
	(0.063)	(0.089)	(0.067)	(0.088)	(0.124)	(0.189)	(0.070)	(0.867)
	{0.868}	{0.808}	{0.802}	{0.868}	{0.868}	{0.802}	{0.986}	{0.802}
Panel B: TOT estimates (IV = village treatment assignment)								
BRAC borrower	1.20	2.28	2.23	1.49	2.64	5.44	0.052	−33.2
	(1.69)	(2.48)	(1.91)	(2.36)	(3.43)	(5.26)	(1.87)	(29.8)
	{0.853}	{0.812}	{0.726}	{0.854}	{0.854}	{0.762}	{0.984}	{0.762}
Panel C: Elasticity								
Amount borrowed from BRAC (log)	0.174	0.332	0.325	0.217	0.385	0.793	0.008	−4.79
	(0.245)	(0.359)	(0.274)	(0.345)	(0.500)	(0.761)	(0.272)	(4.30)
	{0.860}	{0.810}	{0.738}	{0.860}	{0.860}	{0.766}	{0.984}	{0.766}
Control mean at baseline	6.79	6.51	0.714	3.41	4.20	3.12	8.10	53.2
Control mean at baseline (non-zero)		6.59	1.99	3.77	4.41	4.32	8.10	53.2
Baseline level included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3643	3691	3691	3691	3691	3692	3672	4092

Notes
Standard errors are clustered at the village level and shown in parentheses. Westfall–Young p-values for multiple hypothesis testing are shown in braces.
We use 'p.c.e.' to indicate 'per capita equivalent'.
Panel A show ITT results regressing the variable of interest on a dummy variable for whether the respondent lives in a treatment village and a constant. We group all variables in this table for the multiple hypothesis testing. Panel B shows the TOT results by running 2SLS with a dummy taking value 1 if the respondent lives in a treatment village as an instrument for borrowing from BRAC at follow-up. In panel C, the instrumented variable is log(Amount borrowed from BRAC + 1). We control for the level of the outcome variable at baseline and randomization strata. Consumption is a monthly variable constructed from food consumed in the last 7 days, consumer non-durables purchased in the last month, and consumer durables purchased in the last year. Adult equivalent measures count each household member under age 18 as 0.5 adults. Savings is total household savings across all savings methods. 'Total assets' includes the value of all household assets that fall into the categories house, furniture, agricultural assets, business assets, transportation assets. All monetary values are expressed in 2014 USD PPP.
***, **, * indicate significance at the 1%, 5%, 10% level, respectively.

dispersion in consumption across households within a village, using the standard deviation of the log of household consumption. We find a significant reduction in this measure of dispersion in consumption across households in treated villages (the ITT estimate is −0.059, with standard error 0.014).

The remaining columns in Table 11 show no precise evidence of savings increases, asset accumulation or the overall wealth score of households, proxying their permanent income or welfare (column (8)).

Finally, in panel C of Table 11, for the subset of monetary outcomes shown, we report estimates from specification (4). This gives implied elasticities of these outcomes with respect to the size of the last loan from BRAC. We see that the elasticity of total consumption is 0.17, and the elasticity of the value of food consumption with respect to the borrowed amount is 0.33. These elasticities can be benchmarked against other interventions such as cash transfers.

III. Conclusion

Jobs and poverty are tightly linked, and for the bulk of the world's extreme poor, subsistence agriculture lies at the bottom of the job ladder. Occupational diversification is therefore seen as a key way of climbing out of poverty, for both an individual and a country (Buera *et al.* 2021). There is a vast macro literature where movement out of agriculture is an essential component of economic development. But it remains unclear how policy can encourage diversification out of agriculture. Connecting that macro literature that studies structural change to programme evaluation micro literature is an important endeavour.

The microfinance intervention that we study is interesting precisely because it offers capital targeted at encouraging non-agricultural activities in a fairly typical rural African context where households are largely bereft of other sources of formal finance. It is in this type of poor, agricultural setting where the extreme poor are becoming increasingly concentrated even when other parts of the economy may be growing (Page and Pande 2018). It is also where formal financial institutions find it most difficult to operate, given low, infrequent and variable returns from agriculture.

Taking these considerations together, we want to know whether, in this context, microfinance—a core development intervention now reaching 140 million borrowers per year—can encourage household-level diversification out of agriculture and improve welfare. We use a randomized roll-out of the internationally important BRAC microfinance product within households in rural Uganda to answer this question. At baseline, close to 50% of these households are below the extreme poverty line of $1.90 per day, and more than 80% are engaged in subsistence agriculture.

The key result of this paper is that a transfer of capital does encourage diversification into non-agricultural labour market activities but does not improve household welfare. On the extensive margin, women borrowers are setting up non-agricultural business activities such as small-scale trading. On the intensive margin, they put more hours into these non-agricultural labour market activities. In the set of papers summarized in Table 1, only Attanasio *et al.* (2015) and Crépon *et al.* (2020) find an effect of microfinance on movement into self-employment; but neither occurs in a context that is directly comparable to rural Uganda. In fact, the paper that is most akin to our project is Tarozzi *et al.* (2015), which takes place in rural Ethiopia with a similarly unbanked population but finds neither a welfare nor a diversification result.

In our setting, diversification is not, however, associated with improvements in welfare as measured by earnings, consumption, savings, investment or overall wealth. The null effect on overall welfare seems consistent with much of the literature and is confirmed in the meta-analysis of Meager (2019) (Table 1). The types of small-scale trade businesses—such as door-to-door selling and selling food and beverages, textiles and clothing, agricultural inputs and other products in local markets—that women borrowers run are not transformative in terms of improving welfare. As is the case in many of the studies covered in Table 1, these may be the types of businesses that have limited to scope to expand.

Our finding of effects on diversification but with no effects on welfare place the results of this study somewhere between the bulk of the microcredit literature where neither diversification or welfare effects tend to be observed, and the big push literature that finds that bigger capital transfers, sometimes paired with training, are generating effects on both diversification and welfare (Blattman *et al.* 2014; Banerjee *et al.* 2015a; Bandiera *et al.* 2017; Balboni *et al.* 2021). Part of this may have to do with the size of the transfer—the transfer to GDP per capita ratio for Blattman *et al.* (2014) is 81%, and that for Bandiera *et al.* (2017) is 54%, both of which dwarf the 27% observed in this study, which, nonetheless, is on the upper range of loan to GDP per capita values for microfinance interventions (see Figure 1 and Table 1) but still might be insufficient for households to escape a poverty trap (Balboni *et al.* 2021).

It is also natural to ask whether the same resources from the microfinance intervention be better targeted to fewer households. We note that in our results on take-up (Table 7), we have very little predictive power throughout. It is hard to think that based on observables, targeting could be made more efficient. As stated earlier, a promising avenue of current research investigates what drives selection into microfinance and whether potential gains from take-up are known privately to individuals, identifiable by community members or recoverable to the econometrician using machine learning approaches (Beaman *et al.* 2020; Bryan *et al.* 2021; Hussam *et al.* 2021).[13]

Our data allow us to examine only two-year impacts. It would be interesting to monitor how the situation unfolds in rural Uganda to see if the small businesses that have been started or expanded as a result of the arrival of microfinance develop into more significant entities that can affect household welfare over the longer term. Karlan and Zinman (2012) study a longer-run horizon after many loan cycles have elapsed, and perhaps that is when we might see effects on health and education. Also, more recent works suggest that the modest impacts of microfinance are persistent and grow over time, especially for incumbent businesses (Banerjee *et al.* 2019).

Both the low take-up rate for these loans and the null effect on welfare suggest that there is a limited set of business opportunities in these rural contexts. Apart from lack of access to capital, this might also be to do with lack of supporting infrastructure (e.g. roads, electricity, internet), which might constrain the ability of businesses to grow. Our data do allow us to explore this argument a little by examining whether our main effects vary with time to market. We find some evidence that the impacts on labour supply and diversification are weaker in locations that are more distant from markets to begin with.

Whether loans should be directed towards women borrowers (as they are in the bulk of the studies in Table 1) is also an open question. A key feature of microfinance has been the targeting of women on the grounds that, compared to men, they perform better as clients of MFIs, and that their participation has more desirable development outcomes (Pitt and Khandker 1998). The actual evidence for such targeting remains thin. Indeed, a growing literature on micro-entrepreneurship in developing countries has shown that male- but not female-operated enterprises benefit from unconditional cash transfers. A number of explanations have been put forward for this: (i) women are subject to expropriation by husbands (de Mel *et al.* 2008; Jakiela and Ozier 2015); (ii) women are less committed to grow their enterprises or are more impatient (Fafchamps *et al.* 2014); (iii) women sort into less profitable sectors because of unequal labour market access or a preference for flexibility (Bernhardt *et al.* 2019).

Finally, an exciting research frontier in this area is to understand the general equilibrium effects of microfinance. As Buera *et al.* (2020) point out, the effects of microfinance programmes in the short run, which can be substantially positive if programmes are expanded, are materially different from, and even opposite to, the aggregate and distributional effects that microfinance will have in the long run, when scaled up to the entire economy. It important for both research and policy to understand the role that microfinance plays as scale in the macro-economy, whether through aggregate demand, business investment, labour demand, labour diversification or other channels in general equilibrium. A recent literature suggests that these effects are important (Breza and Kinnan 2021; Buera *et al.* 2021). These impacts would in theory be felt most acutely by the world's extreme poor, who are found in rural areas of Sub-Saharan Africa and South Asia, and work in subsistence agriculture (World Bank 2021).

APPENDIX: RESEARCH ETHICS

Following Asiedu *et al.* (2021), we detail key aspects of research ethics related to this study. On policy equipoise and scarcity, there was uncertainty regarding the net benefits from treatment for any given woman. The microfinance intervention under study did not pose any potential harm to participants and non-participants, although concerns over borrowers entering debt traps have been discussed in the literature. The programme implementation was coordinated with the randomization protocol so that after the study was completed, the control group also received the treatment. As randomization was conducted at the village level, all eligible study participants in treated villages could potentially access the intervention. Accessing any of the intervention services was voluntary for study subjects.

The researchers coordinated throughout with the implementing organization, BRAC. The programme roll-out took place according to the evaluation protocol. The researchers did not have any influence in the way the programme was implemented or how microfinance groups were formed. We obtained informed consent from all participants prior to the study. The informed consent included an explanation of the microfinance programme. The consent form also described the research team, and met IRB requirements of explaining the purpose of the study, the participants' risks and rights, confidentiality, and contact information. Research staff and enumerator teams were not subject to additional risks in the data collection process. None of the researchers have financial or reputational conflicts of interest with regard to the research results. No contractual restrictions were imposed on the researchers that would have limited their ability to report the study findings.

On potential harms to participants or non-participants, our data collection and research procedures adhered to protocols around privacy, confidentiality, risk-management and informed consent. Regardless of their access to the interventions, participants were not considered vulnerable (beyond residing in poverty). Participants' capacity to access future services or policies is not reduced by their participation in the study. Besides individual consent from study participants, consultations were conducted with local representatives at the district and community levels.

In each of the four study districts, a separate Memorandum of Understanding was signed, and the Local Council Chairperson (LC1) in each village was consulted before any data collection took place. All the enumerators involved in data collection were recruited from the study districts to ensure that they were aware of implicit social norms in these villages. Summary findings from the project have been presented to district-level authorities, and policy briefs were distributed to the national- and district-level stakeholders. However, no activity for sharing results with participants in each study village is planned due to resource constraints. We do not foresee any risk of the misuse of research findings.

ACKNOWLEDGMENTS

We are grateful to ATAI and an anonymous donor for financial support. We thank Rishabh Malhotra, Menna Bishop, Andre Cazor, Ricardo Dahis, Andre Katz and Maria Ventura for outstanding research assistance, and Orazio Attanasio for helpful discussions.

This project was approved by the LSE Research Ethics Board (REC number 215) and is registered (AEARCTR-0000408).

All errors are our own.

NOTES

1. High repayment frequencies are usually explained by inducing fiscal discipline among borrowers, to overcome costs of monitoring borrowers' actions (Jain and Mansuri 2003), or because borrowers have present-biased quasi-hyperbolic preferences (Fischer and Ghatak 2016). While we have no variation in contractual structures in our setting (beyond households taking loans for 20 or 40 weeks), a growing body of experimental work shows how variation in contractual structures can impact borrower behaviour and outcomes. Feigenberg *et al.* (2013) show how increased frequency of repayment group meetings leads to a higher willingness of borrowers to pool risk with group members, and the returns to such social interactions can then provide an explanation for why group lending reduces default risk. Barboni and Agarwal (2018) show how added flexibility in terms of three-month blocks of repayment holidays chosen in advance attracts more financially disciplined borrowers, and leads to higher repayment rates and improved business outcomes. Battaglia *et al.* (2021) document how increased flexibility, in terms of providing borrowers the option to delay repayments for up to two months during any loan cycle—thus allowing them to respond to shocks more easily—leads to substantial improvements in borrower outcomes, driven by an increase in entrepreneurial risk-taking.
2. BRAC Uganda MFI was later converted into a microfinance bank, allowing them to offer savings services.
3. Ghatak and Guinnane (1999) provide a foundational review of the key mechanisms through which joint liability could improve repayment rates, and other work has highlighted the potential costs of joint liability (Banerjee *et al.* 1994; Besley and Coate 1995; Fischer 2013). More recently, de Quidt *et al.* (2016) have developed and tested a model on which lenders have lower transaction costs under group lending. Group lending constitutes the staple product offered by BRAC in other parts of Uganda: over 96% of existing clients have such loans (Sulaiman 2011). The remaining clients are provided large-scale business loans that require collateral.
4. We can also derive a sense of where these products lie relative to the global microfinance market, not just where RCTs have taken place. Buera *et al.* (2020) use data from the MIX dataset, which provides comparable data from almost 3000 MFIs in 123 countries (Microfinance Information Exchange 2017). The average loan per borrower is \$768 in 2014, with the average loan corresponding to around 97% of GNI per capita.
5. Buera *et al.* (2020) report a comparison of loan sizes to household income (rather than recipient income). If we assume that women in our context contribute half of household income, then the loan size is equivalent to 55% of household income. Buera *et al.* (2020) report that in 2014, the average loan size to income per capita had median 0.27 and a 90/10 split of 1.51/0.06.
6. Consumption expenditures are constructed from food consumed in the last seven days (including both purchased food and valuing home-produced food), consumer non-durables purchased in the last month, and consumer durables purchased in the last year (all converted into monthly expenditure amounts). Total asset value includes the value of all household assets that fall into the following categories: house, furniture, agricultural assets, business assets or transportation assets.
7. These interest rates are derived from household reports of how much they would have to repay hypothetically if they were to borrow 250,000 UGX (\$232) from BRAC. We back out the implied interest rate charged by each credit source, using the formula $A = P(1+r)^t$, where A is the final amount repaid, P is the initial principal, r is the monthly interest rate, and t is the number of time periods (months) elapsed. Given monthly repayments, the implied monthly interest rate is $r = (A/P)^{1/t} - 1$.
8. This evidence reaffirms the notion that MFIs can easily overestimate the demand for their product by not considering this range of alternative sources of credit available to borrowers.
9. A notable exception is Augsburg *et al.* (2015), who study an individual lending programme in Bosnia-Herzegovina (targeted irrespective of gender). The borrowers in the study were chosen to be marginal borrowers based on a scoring model used by the loan officers. Targeting such marginal applicants led to a 100% take-up rate.
10. Beaman *et al.* (2020) find evidence from farmers in rural Mali of selection on gains from microfinance. Farmers with higher returns to capital are much more likely to select—or be selected—into borrowing. This implies that some of the variation in returns is predictable *ex ante*, and that farmers are aware of this heterogeneity in expected returns. Bryan *et al.* (2021) use machine learning using psychometric data to reveal this to be a key driver of heterogeneity in returns to loans to entrepreneurs in Egypt. Hussam *et al.* (2021) find that entrepreneurs in urban India, and their community members, are able to predict which will have the highest returns to capital in their microenterprises.
11. Taken together, the results suggest that any reduction in women's labour supply might have very low output losses given a marginal product close to zero. We have also examined impacts on the labour supply in agriculture for other household members and hired-in labour. We find no effect on (i) other household members helping with agriculture, (ii) the number of hired labourers in agriculture, (iii) expenditure on hired labourers in agriculture, (iv) number of children in school (as we do not have data on child labour directly). These results are also consistent with a low marginal product of female labour in agriculture.

12. The existing evidence on how microcredit impacts consumption is quite mixed. Our results are somewhat in line with the findings of the studies reported in Banerjee *et al.* (2015a), where four studies find null effects. Most other studies find reductions in discretionary spending. The null impacts on health and education spending are more in line with earlier evidence, although in common with other studies, these null impacts are imprecise. At the same time, other studies have documented how many borrowers use microfinance as a consumption loan (Devoto *et al.* 2012; Kaboski and Townsend 2012; Tarozzi *et al.* 2015; Ben-Yishay *et al.* 2017). Kaboski and Townsend (2011, 2012) use Thailand's Million Baht programme as a natural experiment to examine the impacts of microcredit, and are able to probe dynamic responses to a far greater extent than many other studies (including our own). They find evidence that both consumption and incomes go up when the programme is started but then converge back to trend, while asset growth slows down at first and then returns to trend. The magnitudes of the consumption increases that they find are very large, and almost all take the form of durables consumption.
13. The microfinance programme is, however, profitable. While there is cross-subsidization across BRAC branches, it typically takes three to four years for new branch offers to break even from this programme.

REFERENCES

Angelucci, M., Karlan, D. and Zinman, J. (2015). Microcredit impacts: evidence from a randomized microcredit program placement experiment by Compartamos Banco. *American Economic Journal: Applied Economics*, **7**, 151–82.

Asiedu, E., Karlan, D., Lambon-Quayefio, M. and Udry, C. (2021). *A call for structured ethics appendices in social science papers*. Mimeo, Northwestern.

Attanasio, O., Augsburg, B., de Haas, R., Fitzsimons, E. and Harmgart, H. (2015). The impacts of microfinance: evidence from joint-liability lending in Mongolia. *American Economic Journal: Applied Economics*, **7**, 90–122.

Augsburg, B., de Haas, R., Harmgart, H. and Meghir, C. (2015). The impacts of microcredit: evidence from Bosnia and Herzegovina. *American Economic Journal: Applied Economics*, **7**, 183–203.

Balboni, C., Bandiera, O., Burgess, R., Ghatak, M. and Heil, A. (2021). Why do people stay poor? *Quarterly Journal of Economics*, forthcoming.

Bandiera, O., Burgess, R., Das, N., Gulesci, S., Rasul, I. and Sulaiman, M. (2017). Labor markets and poverty in village economies. *Quarterly Journal of Economics*, **132**, 811–70.

Bandiera, O., Burgess, Deserranno, E., Morel, R., Rasul, I. and Sulaiman, M. (2021). *Social incentives, delivery agents and the effectiveness of development interventions*. Mimeo, UCL.

Banerjee, A. V. (2013). Microcredit under the microscope: what have we learned in the past two decades and what do we need to know? *Annual Review of Economics*, **5**, 487–519

Banerjee, A. V., Besley, T. and Guinnane, T. (1994). The neighbor's keeper: the design of a credit cooperative with theory and a test. *Quarterly Journal of Economics*, **109**, 491–515.

Banerjee, A. V., Breza, E., Duflo, E. and Kinnan, C. (2019). *Can microfinance unlock a poverty trap for some entrepreneurs? NBER Working Paper* **no. 26346**.

Banerjee, A. V. and Duflo, E. (2011). *Poor Economics: A Radical Rethinking of the Way to Fight Global Poverty*. New York: Public Affairs.

Banerjee, A. V., Duflo, E., Glennerster, R. and Kinnan, C. (2015b). The miracle of microfinance? Evidence from a randomized evaluation. *American Economic Journal: Applied Economics*, **7**, 22–53.

Banerjee, A. V., Karlan, D. and Zinman, J. (2015a). Six randomized evaluations of microcredit: introduction and further steps. *American Economic Journal: Applied Economics*, **7**, 1–21.

Banerjee, A. V., and Newman, A. (1993). Occupational choice and the process of development. *Journal of Political Economy*, **101**, 274–98.

Barboni, G. and Garwal, P. (2018). *Knowing what's good for you: can a repayment flexibility option in microfinance contracts improve repayment rates and business outcomes?* Mimeo, Warwick University.

Bari, F., Malik, K., Meki, M. and Quinn, S. (2021). Asset-based microfinance for microenterprises: evidence from Pakistan. CSAE Working Paper no. 2021-03.

Battaglia, M., Gulesci, S. and Madestam, A. (2021). *Repayment flexibility and risk taking: experimental evidence from credit contracts*. Mimeo, Trinity College Dublin.

Beaman, L., Karlan, D., Thuysbaert, B. and Udry, C. (2020). *Selection into credit markets: evidence from agriculture in Mali*. Mimeo, Yale University.

Ben-Yishay, A., Fraker, A., Guiteras, R., Palloni, G., Shah, N. B., Shirrell, S. and Wang, P. (2017). Microcredit and willingness to pay for environmental quality: evidence from a randomized-controlled trial of finance for sanitation in rural Cambodia. *Journal of Environmental Economics and Management*, **86**, 121–40.

Berge, L., Bjorvatn, K. and Tungodden, B. (2015). Human and financial capital for microenterprise development: evidence from a field and lab experiment. *Management Science*, **61**, 707–22.

BERNHARDT, A., FIELD, E., PANDE, R. and RIGOL, N. (2019). Household matters: revisiting the returns to capital among female microentrepreneurs. *AER: Insights*, **1**, 141–60.

BESLEY, T. J. and COATE, S. (1995). Group lending, repayment incentives and social collateral. *Journal of Development Economics*, **46**, 1–18.

BLATTMAN, C., FIALA, N. and MARTINEZ, S. (2014). Generating skilled self-employment in developing countries: experimental evidence from Uganda. *Quarterly Journal of Economics*, **129**, 697–752.

BREZA, E. and KINNAN, C. (2021). Measuring the equilibrium impacts of credit: evidence from the Indian microfinance crisis. *Quarterly Journal of Economics*, **136**, 1447–97.

BRYAN, G., KARLAN, D. and OSMAN, A. (2021). *Big loans to small businesses: predicting winners and losers in an entrepreneurial lending experiment*. Mimeo, LSE.

BUERA, F., KABOSKI, J. and SHIN, Y. (2015). Entrepreneurship and financial frictions: a macro-development perspective. *Annual Review of Economics*, **7**, 409–36.

——— (2020). The macroeconomics of microfinance. *Review of Economic Studies*, **88**, 126–61.

BUERA, F., KABOSKI, J. and TOWNSEND, R. (2021). From micro to macro development. *Journal of Economic Literature*, forthcoming.

CAI, S., PARK, A. and WANG, S. (2021). *Microfinance can raise incomes: evidence from a randomized control trial in China*. Mimeo, HKUST.

CASABURI, L. and MACCHIAVELLO, R. (2019). Demand and supply of infrequent payments as a commitment device: evidence from Kenya. *American Economic Review*, **109**, 523–55.

CASABURI, L. and WILLIS, J. (2018). Time versus state in insurance: experimental evidence from contract farming in Kenya. *American Economic Review*, **108**, 3778–813.

CRÉPON, B., DEVOTO, F., DUFLO, E. and PARIENTE, W. (2015). Estimating the impact of microcredit on those who take it up: evidence from a randomized experiment in Morocco. *American Economic Journal: Applied Economics*, **7**, 123–50.

CRÉPON, B., EL KOMI, M. and OSMAN, A. (2020). *Is it who you are or what you get?* Comparing the impacts of loans and grants for microenterprise. Mimeo, CREST.

DE MEL, S., MCKENZIE, D. and WOODRUFF, C. (2008). Returns to capital in microenterprises: evidence from a field experiment. *Quarterly Journal of Economics*, **123**, 1329–72.

DE QUIDT, J., FETZER, T. and GHATAK, M. (2016). Group lending without joint liability. *Journal of Development Economics*, **121**, 217–36.

DEVOTO, F., DUFLO, E., DUPAS, P., PARIENTE, W. and PONS, V. (2012). Happiness on tap: piped water adoption in urban Morocco. *American Economic Journal: Economic Policy*, **4**, 68–99.

EVENSON, R. E. and GOLLIN, D. (2003). Assessing the impact of the Green Revolution, 1960 to 2000. *Science*, **300**, 758–62.

FAFCHAMPS, M., MCKENZIE, D., QUINN, S. and WOODRUFF, C. (2014). Microenterprise growth and the flypaper effect: evidence from a randomized experiment in Ghana. *Journal of Development Economics*, **106**, 211–26.

FAFCHAMPS, M. and WOODRUFF, C. (2017). Identifying gazelles: expert panels vs. surveys as a means to identify firms with rapid growth potential. *World Bank Economic Review*, **31**, 670–86.

FEIGENBERG, B., FIELD, E. and PANDE, R. (2013). The economic returns to social interaction: experimental evidence from microfinance. *Review of Economic Studies*, **80**, 1459–83.

FIALA, N. (2018). Returns to microcredit, cash grants and training for male and female microentrepreneurs in Uganda. *World Development*, **105**, 189–200.

FinScope UGANDA (2009). *Results of a National Survey on Demand, Usage and Access to Financial Services in Uganda*. FinScope Uganda.

FISCHER, G. (2013). Contract structure, risk sharing and investment choice. *Econometrica*, **81**, 883–939.

FISCHER, G. and GHATAK, M. (2016). *Repayment frequency in lending contracts*. Mimeo, LSE.

GHATAK, M. and GUINNANE, T. W. (1999). The economics of lending with joint liability: theory and practice. *Journal of Development Economics*, **60**, 195–228.

HUSSAM, R., RIGOL, N. and ROTH, B. N. (2021). Targeting high ability entrepreneurs using community information: mechanism design in the field. *American Economic Review*, forthcoming.

JACK, W., KREMER, M., DE LAAT, J. and SURI, T. (2016). *Borrowing requirements, credit access, and adverse selection: evidence from Kenya. NBER Working Paper* **no. 22686**.

JAIN, S. and MANSURI, G. (2003). A little at a time: the use of regularly scheduled repayments in microfinance programs. *Journal of Development Economics*, **72**, 253–79.

JAKIELA, P. and OZIER, O. (2015). Does Africa need a rotten kin theorem? Experimental evidence from village economies. *Review of Economic Studies*, **83**, 231–68.

KABOSKI, J. P. and TOWNSEND, R. M. (2011). A structural evaluation of a large-scale quasi-experimental microfinance initiative. *Econometrica*, **79**, 1357–406.

——— (2012). The impact of credit on village economies. *American Economic Journal: Applied Economics*, **4**, 98–133.

KARLAN, D. and ZINMAN, J. (2011). Microcredit in theory and practice: using randomized credit scoring for impact evaluation. *Science*, **332**(6035), 1278–84.

——— (2012). List randomization for sensitive behavior: an application for measuring use of loan proceeds. *Journal of Development Economics*, **98**, 71–5.

MAITRA, P., MITRA, S., MOOKHERJEE, D., MOTTA, A. and VISARIA, S. (2017). Financing smallholder agriculture: an experiment with agent-intermediated microloans in India. *Journal of Development Economics*, **127**, 306–37.

MAITRA, P., MITRA, S., MOOKHERJEE, D. and VISARIA, S. (2021). *Decentralized targeting of agricultural credit programs: private versus political intermediaries*. Mimeo, Boston University.

MCKENZIE, D. (2015). Identifying and spurring high-growth entrepreneurship: experimental evidence from a business plan competition. *World Bank Policy Research Working Paper.*

——— (2018). Can business owners form accurate counterfactuals? Eliciting treatment and control beliefs about their outcomes in the alternative treatment status. *Journal of Business and Economic Statistics*, **36**, 714–22.

MCKENZIE, D. and SANSONE, D. (2019). Predicting entrepreneurial success is hard: evidence from a business plan competition in Nigeria. *Journal of Development Economics*, **141**, 102369.

MCKENZIE, D. and WOODRUFF, C. (2008). Experimental evidence on returns to capital and access to finance in Mexico. *World Bank Economic Review*, **22**, 457–82.

MEAGER, R. (2019). Understanding the average impact of microcredit expansions: a Bayesian hierarchical analysis of seven randomized experiments. *American Economic Journal: Applied Economics*, **11**, 57–91.

——— (2020). *Aggregating distributional treatment effects: a Bayesian hierarchical analysis of the microcredit literature*. Mimeo, LSE.

Microfinance Information Exchange (2017). MIX market database.

MORDUCH, J. (1998). *Does microfinance really help the poor? New evidence from flagship programs in Bangladesh*. Mimeo, Princeton University.

——— (1999). The microfinance promise. *Journal of Economic Literature*, **37**, 1569–614.

PAGE, L. and PANDE, R. (2018). Ending global poverty: why money isn't enough. *Journal of Economic Perspectives*, **32**, 173–200.

PITT, M. M. and KHANDKER, S. (1998). The impact of group-based credit on poor households in Bangladesh: does the gender of participants matter? *Journal of Political Economy*, **106**(5), 958–96.

SULAIMAN, M. (2011). *Borrowing and repayment behaviour of BRAC's clients in Uganda: are there lessons for microcredit in Africa?* Mimeo, BRAC.

TAROZZI, A., DESAI, J. and JOHNSON, K. (2015). The impacts of microcredit: evidence from Ethiopia. *American Economic Journal: Applied Economics*, **7**, 54–89.

UDRY, C. (1994). Risk and insurance in a rural credit market: an empirical investigation in Northern Nigeria. *Review of Economic Studies*, **61**, 495–526

VERA-COSSIO, D. (2021). Targeting credit through community members. *Journal of the European Economic Association*, forthcoming.

World Bank (2008). *World Development Report 2008: Agriculture for Development*. Washington, DC: World Bank.

——— (2021). *World Development Report 2021: Data for Better Lives*. Washington, DC: World Bank.

YOUNG, A. (2019). Channelling Fisher: randomization tests and the statistical insignificance of seemingly significant experimental results. *Quarterly Journal of Economics*, **134**, 557–98.