The Microfinance Business Model:

Enduring Subsidy and Modest Profit

Robert Cull (World Bank)
Asli Demirgüç-Kunt (World Bank)
Jonathan Morduch (New York University)

October 17, 2017

Abstract

Recent evidence suggests only modest social and economic impacts of microfinance. Favorable cost-benefit ratios then depend on low costs. This paper calculates the costs of microcredit and other elements of the microcredit business model using proprietary data on 1,335 microfinance institutions between 2005 and 2009, jointly serving 80.1 million borrowers. The costs of making small loans to poorer clients are high, and when revenues fall short of costs, subsidies are necessary to deliver services to those clients on a sustainable basis. Using a method that accounts for the opportunity costs of all forms of subsidy, the analysis finds that the median institution receives five cents of subsidy per dollar lent and $51 of subsidy per borrower (in PPP adjusted terms). Relatively low levels of median subsidy suggest that even modest benefits of microcredit could yield impressive cost-benefit ratios. The distribution of subsidies is highly skewed, however: the average subsidy per dollar lent is 13 cents and the average subsidy per borrower is $248. The data show that subsidies per borrower are substantially higher for commercial microfinance banks and some non-bank financial institutions that make relatively large loans. MFIs organized as non-governmental organizations (NGOs), in contrast, generally rely less on subsidy.

JEL Codes: 016, G21, H25

Keywords: Microcredit, Nonprofit, Poverty, Implicit subsidy, Cost-Benefit Analysis, Commercialization

The views are those of the authors and not necessarily those of the World Bank or its affiliate institutions. The Mix Market provided the data through an agreement with the World Bank Research Department. Confidentiality of institution-level data has been maintained. We have benefited from comments at presentations at Yale, Princeton, George Washington University, and the World Bank. Morduch acknowledges support from the Gates Foundation through the Financial Access Initiative at NYU. We thank Ippei Nishida and Anca Bogdana Rusu for research assistance.

The Microfinance Business Model:

Enduring Subsidy and Modest Profit

Robert Cull (World Bank)
Asli Demirgüç-Kunt (World Bank)
Jonathan Morduch (New York University)

1. Introduction

Microfinance institutions aim to serve customers ill-served by traditional commercial banks. The success of microfinance in achieving wide scale reach – one count includes 211 million customers globally – has inspired social business initiatives in energy, health, education and other sectors.[1] Microfinance, though, has taken a beating in recent years. Six prominent randomized controlled trials, for example, found only a small average impact of microcredit access on marginal borrowers, though the studies found some "potentially important" (though modest and not clearly robust) impacts on "occupational choice, business scale, consumption choice, female decision power, and improved risk management" (Banerjee et al 2015, p. 14).[2] While perhaps disappointing to microfinance advocates, these modest impacts could nonetheless feed into sizable benefit-cost ratios if the costs are proportionally small too. This is indeed a fundamental premise of microfinance.

[1] Data are as of December 31, 2013, reported as part of the Microcredit Summit's *State of the Campaign Report 2015*. Data are from https://stateofthecampaign.org/data-reported/, accessed 4-15-16.
[2] As Banerjee et al. (2015) describe, the six studies do not provide the final word on microfinance/microcredit impacts. Most important, the studies measure impacts only on marginal borrowers. Some borrowers were determined to be not creditworthy and would have been excluded from being served, for example, but were instead served for the purposes of the study. Other studies measured impacts in new regions for the microlenders, or new populations. Still, earlier studies that did not focus on marginal borrowers or serving new populations have also found relatively modest impacts for microcredit (see, e.g., Armendàriz and Morduch 2010).

By focusing on costs, this study contributes to the missing half of the conversation about the costs and benefits of microfinance.[3] We measure the size of subsidies using proprietary data on 1,335 microfinance institutions between 2005 and 2009. The 930 institutions in the 2009 sample served 80.1 million borrowers globally. Our main findings are that subsidy remains pervasive in the industry, on average representing 13 cents per dollar lent across all types of microfinance institutions (MFIs).[4] The distribution of these subsidies is highly skewed. Borrowers receiving larger loans implicitly receive more subsidy, and, as a result, subsidies per borrower are much higher for commercial microfinance banks and some non-bank financial institutions that make large loans relative to typical MFIs organized as non-governmental organizations (NGOs). Following the literature, we take average loan size as a proxy for target market, with smaller loans typically going to poorer borrowers. Thus, our results suggest that a large share of the total subsidy in microcredit goes to institutions that target less poor borrowers.

Our findings contribute to multiple strands of the existing literature. The first is a methodological contribution to the measurement of subsidy, building on ideas outlined by Yaron (1994). Our data provides more detailed information on the nature of subsidies for a wider sample of MFIs than in past studies, and thus our approach incorporates all of the major types of subsidies (donated equity, borrowing at below-market rates, and in-kind subsidies such as donated equipment, training, or labor) and adjusts them to reflect an appropriate opportunity cost of capital. In contrast, prior studies have used measures of subsidy based on accumulated

---

[3] While we refer to the institutions that we study as 'microfinance institutions,' we acknowledge that our study is only of microcredit and that microfinance can involve other financial services, most notably savings. We use the term 'microcredit' rather than microfinance throughout most of the rest of the paper, except in circumstances where that phrasing would have proved awkward.

[4] Our data precede many of the critiques of microfinance that arose due to over-indebtedness of borrowers (e.g., Andra Pradesh in India) and commercialization (e.g., Compartamos in Mexico). In that sense, the modest profits and enduring subsidies that we find perhaps illustrate the difficulties in maintaining the steady state had the crises mentioned above not occurred, though we acknowledge that the business model continues to adapt and our data do not permit us to analyze fully the most recent adaptations.

donated equity as reported in MFIs' balance sheets (Hudon, 2010; Hudon and Traca, 2011) and/or unclassified donations reported in MFIs' income statements (D'Espallier, Hudon, and Szafarz, 2013, 2017).

An exception is found in D'Espallier, Goedecke, Hudon, and Mersland (2017) [hereafter, DGHM 2017] who calculate a measure of donations (including to equity) and subsidized debt, but for a much smaller sample of 66 MFIs that transformed from NGOs to deposit-taking commercial microfinance banks. The subsidy measure in Caudill, Gropper, and Hartarska (2009) incorporates in-kind donations and donated equity, but does not account for subsidized borrowing. Donated equity is adjusted using local deposit rates to reflect the opportunity cost of capital, but we argue below that those rates are an unrealistically low reflection of the rate that most MFIs would borrow at in the market. Because it incorporates donated equity and subsidized borrowing, and the borrowing component reflects the difference between market and actual interest rates paid, the DGHM (2017) subsidy is most similar to ours, but again neither component is adjusted to reflect opportunity cost, and their sample of MFIs is much smaller than ours.

Our findings also have implications for the literature that links subsidies to the social performance of MFIs. For example, D'Espallier, Hudon, and Szafarz (2013) find that MFIs that receive no subsidies make significantly larger loans and lend significantly smaller shares of their portfolios to women. Subsidies can simply help MFIs cover the high costs of serving poorer clients, but they can also give donors greater influence over managerial decisions (Mersland, 2009). D'Espallier, Hudon, and Szafarz (2017) show that MFIs that face less year-to-year volatility in the subsidies they receive are able to maintain significantly smaller average loan sizes than others, suggesting that predictable subsidies enable and/or compel MFIs to pursue their social mission to serve the poor. DGHM (2017) show that when NGOs are transformed into commercial microfinance banks, their reliance on subsidized funds declines in favor of deposits and commercial debt.[5] While their long-term profitability improves, it comes at the expense of sharp increases in average loan size. Our findings are also consistent with the notion that the slightly higher subsidies that NGOs receive per dollar lent are crucial for them to serve poorer borrowers (who again typically receive smaller loans). And they also show that NGOs have been more effective than other MFIs in holding down costs while serving that target market.

At the same time, there are concerns that subsidies reduce MFIs' incentives to perform efficiently. For example, Caudill, Gropper, and Hartarska (2009) show that MFIs in Eastern Europe and Central Asia that rely more on deposit funding and less on subsidies are more efficient than others over time. In contrast, Hudon and Traca (2011) find that MFIs that receive subsidies are more efficient than those that do not, though that advantage grows smaller beyond a threshold at which marginal efficiency declines with additional subsidy. Seemingly contradictory results could be attributable to a number of factors – subsidies and efficiency are measured differently, and the sample of MFIs varies widely across studies. Still, our findings suggest that it is crucial to account for both organizational type and target market in assessing the trade-offs faced by different types of MFIs.

In that sense, our analysis also contributes to the broader literature on funding and performance trade-offs faced by MFIs. The existing literature provides evidence of a trade-off between the financial sustainability of MFIs and their depth of outreach to typically underserved market segments (Hermes and Lensink, 2011). For example, applying efficiency estimation techniques from the banking literature to a set of 435 MFIs, Hermes, Lensink, and Meesters

[5] Indeed, transformed MFIs may lose access to various types of subsidies, including grants (Mersland, 2009; D'Espallier, Hudon, and Szafarz, 2013).

(2011) show that those that have smaller average loan balances and a higher share of lending to women – both measures of the depth of outreach – are less efficient than others. How subsidies affect such trade-offs has been less studied, though again Hudon and Traca (2011) can be interpreted as showing that subsidies do not compromise efficiency as long as they do not reach excessive levels. And indeed, we show below that, despite receiving slightly more subsidy per dollar lent than more commercially oriented MFIs, NGOs serve the low end of the market more cost effectively than others.

The remainder of the paper is organized as follows. Section 2 describes our data and the method that we use to calculate subsidies. Section 3 uses average loan sizes to summarize the target markets for different categories of MFIs. It then describes how operating costs per dollar lent and the interest rates charged on microloans vary with average loan size. Having described how those components of the microcredit business model interrelate, Section 4 presents measures of the economic (rather than accounting) profitability of the MFIs in our sample under alternative assumptions about the opportunity cost of capital. The share of economically profitable MFIs is low under reasonable scenarios, providing a rationale for subsidies. Section 5 provides our estimates of subsidies and discusses their allocation across the different types of MFIs. Section 6 decomposes our measure of subsidy into its components (donated equity, subsidized borrowing, and other donations) and discusses how the shares of total subsidies attributable to those components varies across MFI types. It also compares the benefits of microcredit found in the literature to the size of subsidies, and then provides rough comparisons between benefit-cost ratios for subsidized microcredit to those for other development interventions. Section 7 offers conclusions.

2. Method and Data

The data are from the global database of microfinance institutions collected by the MIX Market. Within the microfinance sector, the MIX Market is responsible for collecting and disseminating financial data on MFIs, and its database is the largest industry data source on the finances of MFIs. Participation in the MIX database is voluntary, however, and the microfinance institutions in the sample tend to feature institutions that stress financial objectives and profitability (though the database has become more broadly representative as it has expanded over time). To that extent, the data here may understate the level of subsidy in the broader population, and we focus on results conditional on institution-type to try to maintain broader comparability.[6]

The raw data reflect local reporting standards, and the MIX Market adjusts the data to help ensure comparability across institutions when measuring financial performance. We begin with the MIX Market adjustments and then make further adjustments. MIX Market adjustments are made for inflation, the cost of subsidized funding, current-year cash donations to cover operating expenses, donated goods and services, loan write-offs, loan loss reserves and loan loss provisioning. In addition, the MIX reclassifies some long-term liabilities as equity, and reverses any interest income accrued on non-performing loans. We further adjust the data to reflect ideas consistent with economic definitions of profit.

The MIX Market presents a calculation of profitability: i.e., the financial self-sufficiency (FSS) ratio. This notion of financial self-sufficiency is meant to indicate whether an organization can continue operations without external donor funding, but the FSS ratio falls short of accounting for inputs at their opportunity costs. The MIX Market reports that they make a cost-

[6] The skew is shown by Bauchet and Morduch (2010). They first calculate that the average operational self-sufficiency ratio (a measure of organizational efficiency) of institutions reporting to the Microcredit Summit Campaign database, which is larger and socially-focused. The ratio there is 95 percent (scores above 100 percent reflect "operational self-sufficiency."), compared to 115 percent for institutions reporting to the MIX Market.

of-funds adjustment to account for the impact of “soft loans.” The MIX Market calculates “the difference between what the MFI actually paid in interest on its subsidized liabilities and what it would have paid at market terms.” To do that, the MIX Market uses data for shadow interest rates from the IMF’s International Financial Statistics database, using the country’s deposit rate as the benchmark.[7]

The calculation we use differs in two ways.[8] First, we replace the deposit rate with the country’s prime lending interest rate (taken from the World Bank’s *World Development Indicators*).[9] We thus replace the MIX subsidy adjustment with:

Borrowing subsidy adjustment = total borrowing * (prime lending rate) - interest expense on total borrowings.

Second, we add an adjustment for implicit subsidies to equity:

Equity adjustment = Total donated equity amount * (prime lending rate)

This gives us a formula for financial self-sufficiency that embodies the notion of economic profit:

Financial Self-Sufficiency = Financial revenue / [Financial expense + Operating expense + Net loan loss + Net inflation adjustment + Borrowing subsidy adjustment + Equity adjustment].

[7] From MIX Market, “Benchmarks Methodology” http://www.themix.org/sites/default/files/Methodology%20for%20Benchmarks%20and%20Trendlines.pdf.
[8] See online technical appendix for additional details on the derivation of the FSS ratio and how it differs from the measure of financial self-sufficiency used here to calculate subsidies.
[9] Where the prime lending rate is not available in the *World Development Indicators*, we use data from country publications. For example, we take India's rates from the Indian government statistics website (Chapter 24 "Banks, Table 24 Money rates in India"). Available at: http://mospi.nic.in/Mospi_New/site/India_Statistics.aspx?status=1&menu_id=14 ".

Many of the MFIs in our sample also have accounting profits that could be used to defray the subsidies they receive. We therefore subtract those profits from our measure of total subsidy. The measure of total subsidy that we calculate below is, therefore:

Total Subsidy = Borrowing subsidy adjustment + Equity adjustment + In-kind donations – Accounting profits

By using a more appropriate measure of the cost of capital and applying it to equity as well as debt financing, we obtain a clearer view of microfinance profitability and subsidy (see also Yaron 1994 and Manos and Yaron 2009). Our analyses assume that, if they needed to borrow on the market, microfinance institutions could obtain capital at a country's prime interest rate (the rate offered to banks' safest and most favored customers). This is a conservative correction in that it does not reflect the risks of lending to institutions whose loans are typically only partially secured with collateral, and even this adjustment has large effects.[10]

We analyze the most recent data from our sample of MFIs between 2005 and 2009. The entire database includes 3,845 institution-years, reflecting 291 million borrower-years. We focus on a cross-section with the most recent data for each institution.[11] Most of the most recent data are from 2009, a year in which the data include 930 institutions with a combined 80.1 million borrowers.[12]

[10] The other variables that enter our calculations are expressed in nominal terms in local currency and so we use the nominal prime rate as the market rate of interest. In practice, because the nominal prime rate is conservative (since it is extended to the best borrowers), there are few instances of high values. Were we to convert nominal prime rates to real, it would have little effect on the financial sustainability and subsidy calculations for the vast majority of MFIs. Recall also that our calculations already include an inflation adjustment, which is a total (a simple income statement entry) expressed in local currency that also comes directly from the MIX.

[11] Unfortunately, and unlike for other variables derived from MIX data, the subsidy variables that are the focus of our analysis can only be constructed for a handful of years (2-5) for a subset of the MFIs in our sample. For most MFIs we can calculate subsidies for only one or two years. Longitudinal analysis is not therefore feasible given our data.

[12] The work here updates our previous work with smaller, earlier samples of MIX Market data. Cull et al. (2009) use a sample of MIX Market data with 346 microfinance institutions in 67 countries covering nearly 18 million active borrowers, drawn from 2002-4. Cull, Demirgüç-Kunt, and Morduch (2007) analyze 124 MFIs in 49 countries.

The largest sample we use contains data on 1,335 institutions: 90 for-profit commercial banks that provide microcredit, 235 credit unions and cooperatives, 465 NGOs, 401 non-bank financial institutions (NBFIs), and 102 rural banks.[13] Non-bank financial institutions are a broad range of institutions that generally span the space between NGOs and banks, and we divide the sample between institutions with for-profit legal status (300 institutions) and those with not-for-profit status (101 institutions).[14] In addition, we analyze two aggregate categories defined by the MIX Market: 826 institutions with not-for-profit legal status, and 499 institutions with for-profit legal status.[15]

The key relationships are analyzed by comparing means and distributional parameters of subgroups within the sample. A series of LOWESS (non-parametric smoothed) bivariate regressions describe the distributions of the data, and multivariate regressions are used to control for relevant covariates.

A major focus is how key variables like costs, interest rates, and subsidy vary with the average loan size of microfinance institutions. The average loan size variable is a proxy for the income level of customers, drawing on evidence that poorer customers tend to take smaller loans. The variable is measured at the institution-level and is an average of loan sizes that could vary broadly within the institution. To control for different levels of income and development across regions, we normalize the average loan size variable by dividing it by the country's GNI (gross

[13] We acknowledge that our data come from a period when some NGO MFIs were being transformed into NBFIs and commercial microfinance banks, often receiving equity injections and other subsidies to help cover transformation costs. For example, D'Espallier et al., (2017) studies a sample of 66 such transformations. Unfortunately, our data do not enable us to identify whether NBFIs/Banks had recently transformed from NGOs (the MIX provides a single ownership classification for each MFI, and we lack sufficient time series for almost all MFIs in our sample to detect changes in that classification). We can, however, separate older and younger NBFIs/Banks. The subsidies calculated below are smaller for older NBFIs/Banks than for younger ones, but still substantial, indicating that transformations and associated equity injections cannot account for all of the relatively heavy subsidies that we find for NBFIs/Banks.

[14] We take the classification of institutions as it was given to us by the MIX.

[15] Fourteen institutions were dropped: one "bank" with not-for-profit status and 13 rural banks with not-for-profit status. Because all variables are not available for all institutions, sample sizes vary for some analyses. We have repeated the analysis in a balanced panel of 814 institutions and find results very similar to those reported here.

national income) per capita, measured at the 20th percentile. The step of dividing by GNI per capita is relatively standard, but it creates a potential distortion in countries in which there is substantial income inequality, making loan sizes seem relatively small compared to countries at a similar level of average GNI but with lower inequality. We thus normalize by GNI per capita at the 20th percentile of the population to address inequality within countries.[16]

We use the entire sample in regressions (including non-parametric regressions), but we present graphical results only for the segment of the sample containing the bulk of institutions. The figures thus cover normalized loan sizes of 0 through 5. Half of institutions have normalized average loan sizes between 0 and 1. Only a quarter of institutions have normalized average loan sizes larger than 2.5.

3. Average Loan Size, Costs, and Interest Rates

Figure 1 depicts the density of average loan sizes for the three types of institutions that comprise the bulk of our sample: NGOs, non-bank financial institutions (NBFIs) and commercial microfinance banks ("banks"). Since much of our interest is in the pattern of financial variables across institutions in different market segments, we use (normalized) average loan size as a rough proxy for the income level of customers. The NBFIs in the figure combine both for-profit and not-for-profit institutions.[17] NGOs are concentrated heavily at the lowest ranges, between normalized average loan sizes of 0 and 1, with a median of 0.5. NBFIs make larger loans on

[16] At the same time, there are potential limitations and drawbacks of using per capita income of the bottom 20% to normalize loan size. For example, in countries characterized by a high degree of inequality, income at the 20th percentile can be quite low. The normalization will therefore boost normalized loan sizes for MFIs operating in those countries. As robustness checks, we therefore normalized loan size by GNI per capita and we reran our regressions after dropping observations from countries with large gini coefficients (greater than .44). We find similar qualitative results to the ones presented in the paper for those robustness checks.

[17] In the tables that follow, we find that for-profit and not-for-profit NBFIs have similar loan sizes, portfolio yields, and costs per dollar lent. We also cannot reject the hypothesis that the positive relationship between loan size and subsidy per borrower is similar among for-profit and not-for-profit NBFIs in the regressions that follow. To reduce clutter in the figures, we therefore combine both types of NBFIs into a single category.

average (median = 1.1), and banks are still larger (median = 3.4) – at the upper reaches of the sample. There is limited overlap between NGOs and commercial microfinance banks.

Table 1 gives summary statistics on the distribution of average loan size. For the full sample, the average loan size (normalized as described above) is 2.4, but the median is substantially lower at 1.0, reflecting a long upper tail. At the 75th percentile, the normalized average loan size is 2.5, so roughly a quarter of the sample is above the sample mean. Table 1 also shows how average loan size varies across types of institutions. The row on NGOs, for example, shows a median of 0.5, a figure substantially below the median for banks (3.6).[18] As in previous analyses, NGOs and banks look and behave differently, a motivation for the disaggregation here. The mean (normalized average) loan size for banks is 6.9 and the mean for NGOs is 1.4. We asserted that NBFIs span the space between NGOs and banks, consistent with the mean average loan size for for-profit NBFIs of 2.8 and the mean for non-profit NBFIs of 2.4.

Costs

Costs are partly fixed and partly variable. With high fixed costs, larger-sized loans have lower unit costs, giving a cost advantage (all else the same) to institutions making larger loans. Differences in unit costs emerge when disaggregating by average loan size. Figure 2 shows that unit costs are substantially higher when loans are small, reflecting the relatively large fixed costs involved in microcredit operations.[19] Again, NGOs tend to cluster to the left (smaller loans) and commercial microfinance banks tend to cluster to the right, with NBFIs spanning the middle space. Since Table 1 showed that the median normalized loan size across the sample is 1.0, half

[18] Summary statistics vary slightly in the figures and tables since we truncate extreme values in the figures, as described above. The median normalized average loan size for commercial microfinance banks is 3.4 in figure 1, for example, and 3.6 in Table 1.

[19] We acknowledge that large fixed costs only partially explain higher costs per-dollar-lent for small loans since variable costs can also be higher for smaller loans. For example, clients may be harder to get to or may require additional services.

the sample is clustered at the very left end of the figure, where costs are considerably higher than to the right.

Figure 2 also shows that NGOs have brought down costs on the low end, since NGOs have lower costs in the part of the distribution that they dominate (i.e., between a normalized average loan size of 0 and 1). The median commercial microfinance bank makes loans that are, on average, three times larger than the median NGO (after controlling for local conditions). That helps the median commercial microfinance bank reduce unit costs to 11 percent – versus 18 percent for the median NGO.

As we show below, the low-end institutions with higher operating costs also charge higher interest rates. Those higher costs imply that institutions charging higher interest rates are not necessarily more profitable – and below we show that they are not, generally.[20]

Interest Rates

Figure 3 summarizes real (inflation-adjusted) average portfolio yields and thus shows how average loan size matters to the business models of the institutions. This is a measure of average interest rates, calculated by dividing the total interest earnings and fees by the size of the loan portfolio.[21] The figure shows that most real interest rates vary between 20% and 40%, with larger loans under 30% and smaller loans above 30%.[22] In short, institutions making the

[20] A frequent argument is that MFIs that charge higher interest rates tend to be more profitable, and, controlling for other relevant factors in regressions, there is a strong positive relationship between nominal yields and measures of profitability (see, e.g., Cull et al., 2007). However, in our sample, the MFIs that make smaller loans (typically NGOs) have higher yields because the costs of serving their poorer target population is higher per dollar lent. Thus, high yields do not necessarily translate into higher relative profitability for MFIs that target poorer borrowers.

[21] Because our data are drawn largely from the balance sheets and income statements of the MFIs, we have no information on the length of the relationship between individual borrowers and a given institution. However, because microloans tend to be for terms less than one year, dividing total subsidy by the number of active borrowers at any point in time should not create a major distortion, unless borrowers have multiple current loans from the same institution. As a robustness check, we recalculated key figures/tables dividing subsidies by the number of active loan accounts and found very similar qualitative patterns.

[22] Although portfolio yield is widely used as a proxy for the interest rates charged on microloans in the literature, we acknowledge that it carries some limitations. Because it is based on the interest income received by the MFI rather than the interest rate charged to the borrower, it can be affected by how and when interest is accrued and by loan

smallest-sized loans charge the highest average interest rates. Taking average loan size as a proxy for poverty levels, the figure shows that the poorest customers in the microcredit sector pay the highest interest rates.

Consistent with the pattern of costs, NGOs charge more than commercial microfinance banks. After adjusting for inflation, the median microcredit lender charged borrowers 21 percent per year, as measured by the average real portfolio yield (Table 2).[23] NGOs, the institutions that tend to serve the poorest customers, lent at an average of 28 percent per year after inflation. For-profit commercial microfinance banks, in contrast, charged an average of just 22 percent per year. But these averages are deceiving. Once the data are disaggregated by target market (normalized average loan size) in Figure 3, it becomes easier to see to see that commercial microfinance banks charge less because they cluster at larger loan sizes. NGOs charge relatively less when attention is limited to smaller loan sizes. When the scale of loans is considered, commercial microfinance banks are seen to charge higher rates in the markets where NGOs tend to cluster.

In Appendix A, we produce linear versions of the relationships in Figures 2 and 3 with 95% confidence intervals.[24] Those error bars indicate that the differences between commercial microfinance banks are statistically significant for small and large loans, though differences between MFI types are not significant for intermediate normalized average loan sizes. Bi-variate relationships in the figures do not control for many well-known factors that affect portfolio

---

repayment. However, the share of non-performing loans tends to be low in our sample (well below 5% for most MFIs in our sample).

[23] For reference, the average nominal portfolio yield (earnings from lending divided by the size of the loan portfolio) in our sample is 34 percent and the median is 29 percent.

[24] We use the 'twoway lfitci' command in STATA which calculates the prediction for yvar from a linear regression of yvar on xvar and plots the resulting line, along with a confidence interval. As can be seen, the linear relationships in Appendix A are similar to those from the lowess regressions in Figures 2 and 3.

yields which could partially account for the overlaps between types in the figures.[25] We therefore include regressions that enable us to identify more precisely significant differences across types, and also to test whether the quadratic relationship between real portfolio yield and average loan size in Figure 3 holds after controlling for those factors.

We estimate the following equation describing variation in yields:

$$(1)\quad Y_i = \alpha + \beta_1 \text{Avg Loan Size}_i + \beta_2 \text{Avg Loan Size}_i^2 + \beta_3 \text{Region}_i + \beta_4 \text{Age}_i + \beta_5 \text{Assets}_i + \beta_6 \text{Ownership}_i + \beta_7 \text{Ownership*Loan Size}_i + \beta_8 \text{Ownership*Loan Size}_i^2 + \varepsilon_i$$

Where Y_i is the real portfolio yield of microfinance institution *i.* Controls include regional dummy variables; the age and size of each microfinance institution (measured by total assets); and ownership type using the same categories as in the tables presented thus far – commercial microfinance bank (for-profit), credit union/cooperative (not-for-profit), NGO (not-for-profit), NBFI (for-profit), NBFI (not-for-profit), and rural bank. We interact the ownership type indicator variables with average loan size (divided by the per capita income at the 20th percentile of the population) to allow the relationship between loan size and yields to vary across types of institutions. The omitted ownership category is not-for-profit NBFIs. Thus, β_1 and β_2 describe the relationship between loan size and yields for that group of institutions. To assess whether that relationship is significant for other ownership types, we add β_1 to β_7 and β_2 to β_8 (see t-tests at the bottom of the Table 3). β_7 and β_8 also provide tests of the whether the coefficients for the average loan size variables for other ownership types are statistically distinguishable from those for institutions in the omitted category. Standard errors are clustered at the country level.[26]

[25] Because the lowess regressions are intended only to summarize central tendencies, they do not explain substantial variation in variables such as portfolio yields within a given MFI type. Control variables in the regressions that follow are included to help explain that within-type variation.

[26] We conducted robustness checks of key findings using country dummy variables in the regressions, since those better account for country circumstances such as inequality levels and the level of competition in microcredit. We acknowledge, however, that better data is needed to control fully for competition within and among MFI types in a given country, and that competition could explain some of the differences in costs and yields across market segments within the same country.

Table 3 shows that portfolio yields are significantly lower in Europe and South Asia, and for older and larger institutions.[27] In all models, the coefficient for average loan size is negative indicating that interest rates tend to be lower for larger loans. In models 2, 3,, 5, and 7 the square of average loan size is positive, thus confirming the quadratic relationship in Figure 3. In model 7, the lack of statistical significance of the interactions between the ownership type variables and the two average loan size variables indicates that the declining quadratic relationship for not-for-profit NBFIs (the omitted category) holds also for other ownership types. This is also confirmed for NGOs, for-profit NBFIs, and credit unions/cooperatives by the significant t-statistics at the bottom of the table. The patterns are similar for rural banks, but the cell size is small and the coefficients are not estimated with much precision. The exception to the declining quadratic relationship between loan sizes and yields is commercial microfinance banks. Coefficients for their interactions are significant and of the opposite sign as those for not-for-profit NBFIs, and the t-tests at the bottom of the table indicate a marginally significant declining relationship between loan size and yields for banks, but no significance on the interaction with the square of loan size (and thus less evidence of a quadratic relationship). The less pronounced patterns for commercial microfinance banks are also suggested by Figure 3.[28] In any event, model 6, which

In a separate robustness check we recomputed key tables describing the distribution of loan sizes, costs/yields, and subsidies by MFI types for individual regions that had a sufficient number of observations. Those tables generally show that comparisons between MFI types are similar across regions, and thus we believe our focus on differences across types is warranted. To conserve space, these checks are not included in the paper.

[27] A key reason why yields are lower in Europe and South Asia (in addition to the political and regulatory environment) is that the MFIs operate in more densely populated areas. This is also reflected in unreported regressions that use operating costs per dollar lent as the dependent variable.

As a robustness check, we reran the regressions in Table 3 and those that follow in Table 5 after dropping observations from South Asia, since that coefficient is especially large (in absolute value). Qualitative results for key variables such as loan size remain similar.

[28] Commercial microfinance banks could be the exception to the declining quadratic relationship in the regressions because we have too few observations on the left hand side of the graph (i.e., small average loan sizes) to estimate the relationship precisely. However, the pattern for that group's coefficients is the same as that for other groups (a net negative for average loan size, positive for its square), but the magnitudes are smaller (in absolute value). The

does not include the interactions with the square of average loan sizes, confirms a significant negative relationship between portfolio yield and average loan size for commercial microfinance banks.

For brevity, we do not show regressions that use operating costs per dollar lent as the dependent variable. However, similar to the regressions for portfolio yields, those unreported regressions show a quadratic relationship between operating costs per dollar lent and average loan size for almost all MFI types. That the regression models for both portfolio yields and operating costs line up well with each other indicates that they are describing related aspects of the business models used by different institutions, and the environments in which they operate (as reflected in the significant coefficients for the control variables).

4. Profitability

Profitability is crucial for assessing whether the benefits of providing microcredit exceed its costs from the perspective of the providers, and therefore speaks to whether the benefits of microcredit can be delivered to clients in a financially sustainable manner. In those cases where costs exceed revenues (and we discuss the types of institutions and target markets for which this is more likely), microcredit cannot be delivered without subsidy.

Changes in profitability of MFIs under different assumptions about the opportunity cost of capital can be seen in Figure 4. It begins with the left-most pair of columns showing that, in terms of basic operational sustainability (as measured by the ratio of revenues to costs), 67 percent of institutions in the MIX Market sample would be seen as profitable on an accounting basis. The figure is weighted by the number of borrowers per institution, so it says that two-thirds of microcredit borrowers were served by institutions earning accounting profits. Just 58

---

slope of the yield/loan size curve on the left side of Figure 3 was also less steep for commercial microfinance banks than the other MFIs.

percent were profitable on an accounting basis when institutions are weighted instead by their assets.

The second set of columns in Figure 4 uses the MIX Market's measure of profitability, the financial self-sufficiency (FSS) ratio. As described above, the FSS captures the difference between revenues and costs, with adjustments made to account for some implicit subsidies. The adjustments that the MIX Market makes in calculating FSS take the percentage that appear profitable to just over half (weighted by the number of borrowers per institution; just 42 percent of institutions were profitable by this definition when weighted by their assets).[29] But as noted, the calculation does not adequately account for the opportunity cost of the institutions' equity and debt.

The third pair of columns makes a modest adjustment, assuming that the appropriate opportunity cost of capital should be given by the US prime lending rate. The perspective is that the donors, most of which are based in richer countries like the US, might see that as their benchmark for lending in the market. Even with this modest adjustment, now only roughly 45 percent of the sample is seen as profitable (weighted by the number of borrowers per institution; just 30 percent were profitable by this definition when weighted by their assets). In the final pair of columns, the most realistic assumption is used: the prime rate in the institutions' local market. This accommodates local inflation and the ability to raise money on local markets. Now, the percentage of institutions that are profitable falls to 36 percent when weighted by borrowers and just 18 percent when weighted by assets.[30]

[29] The finding that a large share of MFIs have profits near zero has been noted in the literature (See, e.g., Hermes and Lensink, 2011, p. 878).
[30] We acknowledge that many social investors are content with receiving risk-adjusted returns on their investments in microfinance that are below market rates. To the extent that those investors would be willing to do this in perpetuity, more MFIs could be considered financially self-sustaining than when we apply the prime rate to calculate subsidy. Still, the goal of our exercise is to understand how many MFIs would be self-sustaining if they were forced to rely on local capital markets for their funding.

It is sometimes argued that larger institutions tend to be more profitable than smaller ones. Thus, while there may be many unprofitable institutions, most people are served by profitable institutions and most assets are held by profitable institutions.[31] That possibility is not borne out in the data. The final result shows that, rather than being commercially viable, just over two-thirds of microfinance borrowers are served by institutions not earning economic profit, and roughly 80 percent of assets in the sector are held by institutions that are not truly profitable. Even though the institutions are deemed “financially self-sufficient” or close to it, there is still substantial subsidy running through the sector once the shadow cost of capital is defined at a realistic level and applied broadly across financial categories.[32]

5. Subsidies

To calculate subsidy, we use the local prime rate, with the idea that the institution would have to turn to local sources for financing if soft loans were not available. The local interest rates reflect regional economic conditions, and they allow us to abstract from currency risk, political risk, and similar concerns when making cross-country financial comparisons. The second important step is to account for returns to equity, again using the local prime rate. In the MIX Market’s FSS calculations, it is assumed that equity donations get zero real return (the only adjustment is for inflation).

We also note that charging below-market rates does not imply that social investors lose money on their microfinance investments. We thank a referee for pointing out that large institutions such as Oikocredit borrow funds at around 2% and lend them to MFIs at 7%.

[31] Previous work has found strong links between the size of an MFI and its profitability in regressions (see, e.g., Cull et al., 2007).

[32] Commercially-oriented MFIs may be making risky, long-run bets designed to generate large future profits. By focusing on the first five or so years of data for those MFIs, we may underestimate their profitability going forward, and thus overestimate the need for future subsidy. At the same time, when we focus on for-profit MFIs that have operated for at least 10 years below, we find moderately lower subsidies (and slightly higher profitability levels) than those with less experience. This casts some doubt on the ‘long-run bets’ hypothesis.

Table 4 shows subsidy per borrower across institutional types assuming lenders and equity holders would receive a market return as reflected in the local prime rate. We use purchasing power parity (PPP) exchange rates to calculate subsidies on a consistent basis across countries. The sample mean is $248 and the median is $51.[33] For commercial microfinance banks, the mean is $578 and the median is $215, while for NGOs, the mean is $174 and the median is $51. For-profit microfinance institutions as a group receive more subsidy per borrower on average, relative to not-for-profits ($316 versus $207), but the picture switches with the medians ($27 versus $61). The data show that there are some heavily subsidized for-profit institutions, but most for-profits are only modestly subsidized. Still, most for-profits are subsidized.

Figure 5 explores the relationship between subsidy per borrower and the target market of different types of institutions. All types show a clear upward-sloping, nearly linear relationship, such that those offering the largest-sized loans end up more heavily subsidized than those making the smallest loans. The subsidy per borrower stretches toward $500 for commercially oriented institutions making the largest sized loans (commercial microfinance banks and NBFIs). However, NGOs receive substantially less subsidy per borrower than commercial microfinance banks throughout the range of average loan sizes, and less than NBFIs throughout most of the range.[34]

We use regressions to test whether the bi-variate relationships between subsidies and our proxy for target market (normalized average loan size) hold when we control for additional

---

[33] Similar patterns emerge when we use official exchange rates in the subsidy calculations, except that subsidy levels are about half as large. For example, the mean subsidy per borrower is $132 and the median is $26 for the sample. Qualitative comparisons across MFI types are, however, very similar no matter which of the two types of exchange rates we use. See Table 4a in part B of the online technical appendix for a version of Table 4 that uses official exchange rates to calculate subsidies.

[34] One reason why commercial microfinance banks and some NBFIs receive more subsidies is that the largest lenders to the microfinance sector only deal with large MFIs. Some of those lenders are also investors that seek equity positions with put options, something NGO MFIs cannot legally offer.

variables that could account for the level of subsidies received by microfinance institutions. The equation that we estimate is:

(2) $Subsidy_i = \alpha + \beta_1 Avg\ Loan\ Size_i + \beta_3 Region_i + \beta_4 Age_i + \beta_5 Assets_i + \beta_6 Yield/Cost_i + \beta_7 Ownership_i + \beta_8 Ownership*Loan\ Size_i + \varepsilon_i$

The dependent variable, *Subsidy*, is measured as average subsidy per borrower for microfinance institution *i*. The subsidy calculations use the local prime lending rate as the shadow cost of capital, as described above in the text. As in the regressions relating average loan size and portfolio yields, we include dummy variables for different ownership types, and we also interact those variables with normalized average loan size, our proxy for target market. Similarly, we include regional dummy variables and the age and size of each institution as control variables. In our fullest specifications, we include portfolio yields, the ratio of operating costs to assets, and the ratio of capital costs to assets as explanatory variables. These controls are routinely used in regression analyses describing microfinance profitability, portfolio quality, and other outcomes.[35]

The positive relationship between normalized average loan size and subsidy per borrower that was shown in Figure 5 is confirmed in models 1 and 2 of Table 5. When we introduce interactions between ownership type and average loan size in models 3 and 4, the coefficient for loan size declines from $36-37 to $7-8. This indicates that subsidies per borrower are increasing with loan size for institutions in the omitted category (not-for-profit NBFIs), but at a slower rate than for other ownership types. However, the insignificant coefficients on most of the interactions imply that a similar relationship holds for commercial microfinance banks, credit unions/cooperatives, for-profit NBFIs, and rural banks.[36] The exception is for NGOs, whose interaction with loan size has a large and significant positive coefficient ($69-70). Recall from

[35] See for example Cull et al. (2007).

[36] The positive relationship between subsidy per borrower and loan size for institutions such as cooperatives could be because donors purposely shy away from the smaller cooperatives that tend to make small loans.

Figure 1, however, that the largest mass of loans extended by not-for-profit NGOs is 0 to 1 times the per capita income of the bottom 20%. This suggests a modest level of subsidy for the vast majority of borrowers from NGOs.

To this point, we have not emphasized the coefficients on the ownership indicator variables themselves (because they tend to be insignificant), but the large coefficient for commercial microfinance banks ($166-174) in models 3 and 4 bears mentioning. It suggests that, on average, subsidy per borrower is high for loans of all sizes for that group, and it increases at about the same rate as for other types of institutions (except NGOs) based on the coefficients for the average loan size variables. Since Figure 2 also shows that a large share of commercial microbank loans extend beyond their median loan size of 3.4 times the per capita income of the bottom 20%, the regressions indicate that some borrowers from commercial microfinance banks are receiving large loans and a high level of total subsidy.

We note that when subsidy is measured on a per dollar lent basis, it is slightly higher for less commercially oriented MFIs than others. For example, NGOs have an average subsidy per unit lent of 18 percent and a median of 8 percent in our sample. In contrast, commercial microfinance banks have a mean of 15 percent and a median of 8 percent.[37] While NGOs receive slightly larger subsidies per dollar lent, the important point is that the range across all types of MFIs for that variable is narrow. Since average loan sizes vary widely across types (with more commercially oriented, for-profit institutions making substantially larger loans), subsidies per borrower tend to be much larger for those institutions. In addition, within the market that NGOs typically target (normalized average loan size between 0 and 1), they receive substantially less subsidy per dollar lent than commercial microfinance banks (see Figure 6). Subsidies are likely

[37] The median level of subsidy per unit lent in the full sample is 5 percent and the average is 13 percent, indicating that both NGOs and commercial microfinance banks receive more subsidy per dollar lent than other MFI types.

higher for commercial microfinance banks that target this market because, as was shown in Figure 2, their costs are substantially higher than those for NGOs and NBFIs.

Our data also show that subsidies decline as institutions age, but they remain important over time in microfinance, even for older institutions.[38] Summing across the 1335 institutions in our sample, the total subsidy – both explicit and implicit – was $4.9 billion per year.[39] Of the total subsidy, 76% went to the 932 institutions that are older than ten years. The findings contrast with arguments that microfinance subsidies are transitional. Subsidies should play a role in helping institutions get started, according to the argument, but they should phase out within a decade, allowing the unsubsidized market to take over.[40]

6. Discussion

a. Subsidy Breakdown

To give readers a better sense of the importance of the components of our subsidy measure, Table 6 breaks down the average shares of subsidy in the form of donated equity, subsidized borrowing, and in-kind donations. Across all types of MFIs, in-kind donations comprise only 1-3% of subsidies received. On average, subsidized borrowing represents at least 67 percent of total subsidies received, though that average share exceeds 90 percent for commercial microfinance banks and rural banks. Less commercially oriented MFIs receive more of their subsidies in the form of donated equity. NGOs, credit union/cooperatives, and not-for-profit NFIs receive 27-33 percent of their subsidies through such donations. However, the median subsidy shares attributable to donated equity in column 7 are smaller for those

[38] For reference, the mean subsidy per borrower in our sample is $172 for MFIs younger than ten years old, $106 for those ten years or older. While older MFIs rely on somewhat less subsidy than younger ones, our data do not enable us to analyze whether this is due to changing target markets, cost savings over time, or other considerations because we lack a sufficiently long time series.

[39] Again, the calculation uses the most recent observation in the period for each institution.

[40] Of course, an exception is made for subsidies targeted to institutions serving the poorest and costliest to serve customers.

institutions (8-14 percent), indicating the high average shares in column 4 are driven by a subset of the institutions in those groups. In general, however, the ability to borrow at below-prime rates accounts for most of the subsidies that we calculate across all types of MFIs.

Recall that we subtract profits when calculating our final measure of subsidy because those could be used to defray the donations and subsidized borrowing that MFIs rely on. For MFIs with profits that exceed those forms of subsidy, we set our subsidy measure to zero. We do this because the underlying question we are addressing is the extent to which MFIs in developing countries could function in local capital markets without relying on subsidy. The ratio of profits to subsidized borrowing plus donations received (column 10) is, therefore, also an instructive indicator of whether the subsidy dependence of different types of MFIs is warranted. The ratio of profits to subsidies is substantially higher for commercial microfinance banks and NBFIs than NGOs.[41] So not only is total subsidy in microcredit tilted toward those institutions, profits could potentially cover a higher share of the subsidies they receive than profits could cover for less commercially oriented MFIs such as NGOs. This, too, suggests that subsidy could be better allocated toward MFIs that target harder-to-serve markets and thus find it more difficult to generate sufficient revenues to cover the associated costs.

b. Benefit-Cost

In a final exercise, we compare the benefit-cost ratios for microcredit to those of other recently studied development interventions. Since microcredit is partly, or even largely, financially self-sustaining for most institutions (as shown above), we compare its benefits to our estimates of subsidies. For estimates of the benefits of microcredit, we return to the six

[41] The median ratio of profits to subsidies is especially high for credit unions/cooperatives and rural banks in Table 7. For rural banks, this is because subsidies are miniscule (see Table 4). Credit unions/cooperatives receive more subsidies and their sample size is larger than for rural banks, so a high ratio of profits to subsidies is a more meaningful indicator for that group.

randomized control trials in Banerjee et al. (2015). As comparators we use benefit-cost ratios summarized in two recent papers: McKenzie (2017) for vocational training programs and Buera, Kaboski, and Shin (2016) for grants to the ultra-poor. In large part, we choose these comparators because those papers provide a consistent basis for comparing benefit-cost ratios across a relatively large number of studies. At the same time, similarities and differences between those types of interventions and microcredit provide potentially instructive context when comparing benefit-cost ratios.

We first compare the results from the six microcredit studies in Banerjee et al. (2015) with those from seven studies of training programs in Table 1 of McKenzie (2017) that reported (1) program cost and (2) the resulting change in monthly income, and that had (3) a timeframe from baseline to endline surveys similar to those for the microcredit studies (12-24 months).[42] One caveat is that the estimates of net income benefits to microcredit borrowers are not statistically significant, though Banerjee et al. (2015) point out that the point estimates tend to be positive. Positive changes in some components of total income, such as income from self-employment, are also significant in some of the microcredit studies.[43] At the same time, the 95% confidence intervals shown in McKenzie (2017), Table 1, for impact on earnings include zero for four of the seven studies of vocational training that we use for comparison. Thus, imprecise estimates of impact on incomes are found for interventions other than microcredit.

And there are well-known reasons why income effects are imprecisely estimated in microcredit evaluations to date. Most prominently, modest take-up rates that are difficult to

[42] Those studies are Hirshleifer et al. (2016) for Turkey, Alzúa et al. (2016) for Argentina, Attanasio et al. (2011) for Colombia, Card et al. (2011) and Ibarrán et al. (2014) for the Dominican Republic, Maitra and Mani (2012) for India, and Honorati (2015) for Kenya.

[43] Improvements in income may not be the only benefits that microcredit provides. By improving borrowers' ability to manage their financial lives, microcredit can help them meet emergencies with less disruption (Collins, et al., 2009). Microfinance also contributes to overall financial development which has been shown to increase economic growth (see, e.g., Levine, 2005), though we acknowledge that microfinance tends to be small relative to the formal banking sector except in certain notable countries such as Bangladesh and Peru.

predict ex-ante pose a statistical power challenge. In addition, microcredit interventions are typically targeted to marginal borrowers (in terms of ability to repay), whereas benefits may be larger for infra-marginal borrowers (Wydick 2016). Even among marginal borrowers, effects are quite heterogeneous, which further highlights the potential benefits of targeting to borrowers poised to make the largest gains in income.

Although the impacts of microcredit on borrower incomes are modest in Table 7, they are not necessarily small in comparison to the subsidies that we have calculated. Almost all of the microcredit studies in Banerjee et al. (2015) partnered with MFIs organized as NGOs and so we rely on the median subsidy to NGOs in our benefit-cost calculations.[44] We provide two benefit-cost ratios, one based on the median subsidy per dollar lent by NGOs (7.6%), the other on their median subsidy per borrower ($26).[45] Both approaches yield a similar range of benefit-cost ratios across studies.

For the vocational training programs in Table 7, benefit-cost ratios range from .01 to .18 and the average is .05. Excluding the study with the highest ratio, no other produced a benefit cost ratio above .05 and the average was roughly .02. As McKenzie (2017) notes, "[T]he cost of these programs averages 50 times the monthly income gain. Even adjusting for incomplete take-up (which means not having to pay the full costs for people who drop out), it will typically take three or four years at least for participants to recoup in income gains the cost of the program." As

[44] The exception is Angelucci et al. (2015) which partnered with *Compartamos*, a commercially oriented microfinance bank well known for charging high interest rates to its borrowers (Cull et al., 2009). At the same time, its commercial orientation also likely implies that *Compartamos* relies on less subsidy than the NGO MFIs in our sample. The absence of income benefits for borrowers of that program could, therefore, be attributable to those high interest rates. We include that study in Table 7 and in the averages we calculate for completeness, but we recognize that its inclusion biases our overall benefit-cost ratio for microcredit interventions downward. See Cull and Morduch (forthcoming) for discussion of these impact studies and their broader context.

[45] In calculating the cost of microcredit subsidies using the subsidy per dollar lent estimate for NGOs, we therefore multiply 0.076 by the average loan size used in the impact study in question. Calculating costs using the subsidy per borrower estimate for NGOs, we simply convert $26 into local currency. These figures are not PPP-adjusted (see footnote 32). This is because benefits are in local currencies, and thus not PPP-adjusted, in the microcredit studies that we use for these comparisons.

a result, positive benefit-cost calculations for these programs require making assumptions about "the trajectories of impact lasting for periods beyond which impacts have typically been measured." For the microcredit interventions, the benefit-cost ratios range from -0.02 to 0.53 and the average is 0.24 when subsidy is calculated per dollar lent (using the alternative calculation based on subsidy per borrower, the average is 0.30 per borrower). The ratios imply that the income benefit of microcredit exceeds the costs of subsidies if the income gains persist for roughly four months.

Favorable benefit-cost comparisons for microcredit could merely reflect that vocational training programs are ineffective development interventions. We therefore also compare microcredit interventions to those that offer grants to the ultra-poor as part of multi-faceted programs to "establish sustainable self-employment activities and generate lasting improvements in their well-being" (Banerjee, Duflo, et al., 2015). Such programs typically provide a grant to purchase a productive asset, training and support, life skills coaching, temporary cash consumption support, access to a savings account, and health information or services. The comparison with microcredit provided by NGOs is potentially instructive because both types of interventions target similar populations. But they do so in different ways. The grant programs are much costlier than subsidies to microcredit, and their aim is to produce fundamental change in the economic lives of the ultra-poor. Modest subsidies to microcredit realistically should be expected to achieve more modest changes in living standards, but those changes might also take much less time to manifest themselves.

The grant programs summarized in Table 7 have been hailed as a success from a benefit-cost perspective (Buera, Kaboski, and Shin, 2016).[46] And indeed, if one assumes that the

[46] In Table 7 we include all studies on grants to the ultra-poor from Table 2 of Buera, Kaboski, and Shin (2016), for which a benefit-cost ratio could be calculated. Note that benefits are measured in terms of increases in consumption

discounted consumption benefits of these programs extend in perpetuity, benefits are five times greater than costs for the most successful programs. But even the most successful program, BRAC's "Targeting the Ultra-Poor Program" in Bangladesh, achieves a benefit-cost ratio of 0.82 after five years of consumption benefits. Favorable benefit-cost ratios therefore hinge on making assumptions about the trajectory of benefits into the future. Although the benefits are admittedly less precisely estimated for microcredit, they exceed the cost of subsidies within a much smaller window of time, and thus do not require the same assumptions about future benefits. From a simple benefit-cost perspective, therefore, we argue that the comparison does not tilt heavily in favor of multi-faceted grant programs for the ultra-poor or microcredit.

7. Conclusion

The microfinance business model is challenging by definition: If achieving success was possible with standard banking procedures and products, there would be no need for microfinance. The finding that subsidies are relatively large and enduring for some commercial microfinance institutions does not imply that microfinance commercialization is a failure or that investors should turn from microcredit. But it reinforces the need for cost-benefit determinations, and it poses a challenge for the narrative that subsidies are helpful at first but will naturally disappear over time.

The greatest challenge is that the long-standing rhetoric on subsidies and commercialization – which generally argues against the continued use of subsidies – appears to be consistently out of alignment with realities in practice. Having a transparent conversation about the uses and patterns of subsidies is an important step to making sure that subsidies are being used optimally. By tilting away from poorer customers who may be able to benefit most

rather than income. In contrast to these programs, Bauchet et al (2015) find that a similar program in south India failed to deliver positive net benefits.

from subsidies, microfinance subsidies support institutions that may be worthy of support, though perhaps not the most worthy, at least from the vantage of traditional social analysis.

The findings also point to the importance of pursuing new ways to change the cost structure faced by most microfinance institutions. Digital payments and innovations like mobile money have the potential to create business models that allow for reaching the poorest customers sustainably (Gates and Gates 2015). If hopes prove real, they may provide the elusive path for microfinance to reach its promise as a "social business."

Finally, the finding that per-borrower subsidies are in fact relatively small for parts of the NGO sector, especially those institutions making smaller loans, reinforces the need for cost-benefit analyses to complement impact studies. Because our cost calculations are averages across all borrowers, they help place into context pessimistic conclusions from impact studies of marginal borrowers (e.g., Mossman 2015). In addition, the sheer scale of microfinance relative to other development interventions could mean that seemingly small benefits to the average borrower translate into large overall impacts. In some cases, therefore, the findings on cost and subsidy may even reverse the pessimistic conclusions from impact studies.

References

Armendàriz, Beatriz and Jonathan Morduch (2010). *The Economics of Microfinance*, Second edition. Cambridge, MA: MIT Press.

Banerjee, Abhijit, Esther Duflo, Nathaniel Goldberg, Dean Karlan, Robert Osei, William Parienté, Jeremy Shapiro, Bram Thuysbaert, and Christopher Udry (2017). "A Multifaceted Program Causes Lasting Progress for the Very Poor: Evidence from Six Countries." *Science* **348**, 1260799. DOI: 10.1126/science.1260799.

Banerjee, Abhijit, Dean Karlan, and Jonathan Zinman (2015). "Six Randomized Evaluations of Microcredit: Introduction and Further Steps." *American Economic Journal: Applied Economics* 7(1): 1–21.

Bauchet, Jonathan and Jonathan Morduch (2010). "Selective Knowledge: Reporting Bias in Microfinance Data." *Perspectives on Global Development and Technology* 9 (3-4): 240-269.

Bauchet, Jonathan, Shamika Ravi, and Jonathan Morduch (2015). "Failure vs Displacement: Why an innovative anti-poverty program showed no net impact in South India." *Journal of Development Economics* 116: 1-16.

Besley, Timothy. (1994). "How Do Market Failures Justify Interventions in Rural Credit Markets?" *World Bank Research Observer* 9 (1):27-47. doi: 10.1093/wbro/9.1.27.

Buera, Francisco, Jospeh P. Kaboski, and Yongseok Shin (2016). "Taking Stock of the Evidence on Micro-Financial Interventions." National Bureau of Economic Research Working Paper 22674.

Caudill, Steven B., Daniel M. Gropper, and Valentina Hartarska (2009). "Which Microfinance Institutions Are Becoming More Cost-effective with Time? Evidence from a Mixture Model." *Journal of Money, Credit, and Banking* 41:651-672.

Collins, Daryl, Jonathan Morduch, Stuart Rutherford, and Orlanda Ruthven (2009). *Portfolios of the Poor: How the World's Poor Live on $2 a Day*. Princeton, NJ: Princeton Univ. Press.

Conning, Jonathan and Jonathan Morduch (2011). "Microfinance and Social Investment." *Annual Review of Financial Economics*, vol. 3, ed. Robert Merton and Andrew Lo. 2011: 407-434.

Cull, Robert and Jonathan Morduch (forthcoming). "Microfinance and Economic Development," in (eds.), Thorsten Beck and Ross Levine. *Handbook of Finance and Development*. Cheltenham, UK: Edward Elgar.

Cull, Robert, Asli Demirgüç-Kunt, and Jonathan Morduch (2007). "Financial Performance and Outreach: A Global Analysis of Leading Microbanks." *Economic Journal* 117(517): F107-F133.

Cull, Robert, Asli Demirgüç-Kunt, and Jonathan Morduch (2009). "Microfinance Meets the Market." *Journal of Economic Perspectives* 23(1): 167-192.

D'Espallier, Bert, Jann Goedecke, Marek Hudon, and Roy Mersland (2017). "From NGOs to Banks: Does Institutional Transformation Alter the Business Model of Microfinance Institutions?" *World Development*, 89: 19-33.

D'Espallier, Bert, Marek Hudon, and Ariane Szafarz (2013). "Unsubsidized Microfinance Institutions." *Economics Letters* 120(2): 174-176.

D'Espallier, Bert, Marek Hudon, and Ariane Szafarz (2017). "Aid Volatility and Social Performance in Microfinance." *Nonprofit and Voluntary Sector Quarterly*, 46(1): 116-140.

Epstein, Keith (2007). "Microfinance Draws Mega-Players: Hedge Funds, VCs and Other Investors are Seeing the Huge Profit Potential in Tiny Loans." *Business Week*, July 9 and 16, pp. 96-97.

Gates, Bill and Melinda Gates (2015). "Our Big Bet for the Future: 2015 Gates Annual Letter. Bill & Melinda Gates Foundation. http://www.gatesnotes.com/2015-Annual-Letter.

Helms, Brigit. (2006). *Access for All: Building Inclusive Financial Systems* (An Excerpt). Washington DC: CGAP.

Hermes, Neils and Robert Lensink (2011). "Microfinance: Its Impact, Outreach, and Sustainability." *World Development* 39(6): 875-881.

Hermes, Neils, Robert Lensink, and Aljar Meesters (2011). "Outreach and Efficiency of Microfinance Institutions." *World Development* 39(6): 938-948.

Hoff, Karla and Andrew Lyon. (1995). "Non-leaky Buckets: Optimal Redistributive Taxation and Agency Costs." *Journal of Public Economics* 58: 365-390.

Hudon, Marek (2010). "Management of Microfinance Institutions: Do Subsidies Matter?" *Journal of International Development* 22: 890-905.

Hudon, Marek and Daniel Traca (2011). "On the Efficiency of Subsidies in Microfinance: An Empricial Inquiry." *World Development* 39(6): 966-973.

Levine, Ross (2005). "Finance and Growth: Theory and Evidence," in *Handbook of Economic Growth*. Philippe Aghion and Steven Durlauf, Eds. Amsterdam: North-Holland Elsevier Publishers.

Lützenkrichen, Cédric. (2012). *Microfinance in Evolution.* Deutsche Bank: DB Research.

Manos, Ronnie and Jacob Yaron. (2009). "Key Issues in Assessing the Performance of Microfinance Institutions." *Canadian Journal of Development Studies* 29(1-2): 99-122**.**

McKenzie, David (2017). "How Effective Are Active Labor Market Policies in Developing Countries? A Critical Review of Recent Evidence." World Bank Policy Research Working Paper 8011.

Mersland, Roy. (2009). "The Cost of Ownership in Micro-Finance Organizations. *World Development* 37(2): 469-478.

Morduch, Jonathan (1999). "The Role of Subsidies in Microfinance: Evidence from the Grameen Bank," *Journal of Development Economics* 60: 229 - 248.

Mossman. Matt. 2015. "Moving Beyond Microcredit." *The New Yorker*. November 2, 2015.Schreiner, Mark and Jacob Yaron (2001). *Development Finance Institutions: Measuring their Subsidy*. Washington, DC: The World Bank.

Wydick, Bruce (2016). "Microfinance on the Margin: Why Recent Impact Studies May Understate Average Treatment Effects." *Journal of Development Effectiveness* 8(2): 257-265.

Yaron, Jacob (1994). "What Makes Rural Finance Institutions Successful?" *World Bank Research Observer* 9 (1): 41-70.

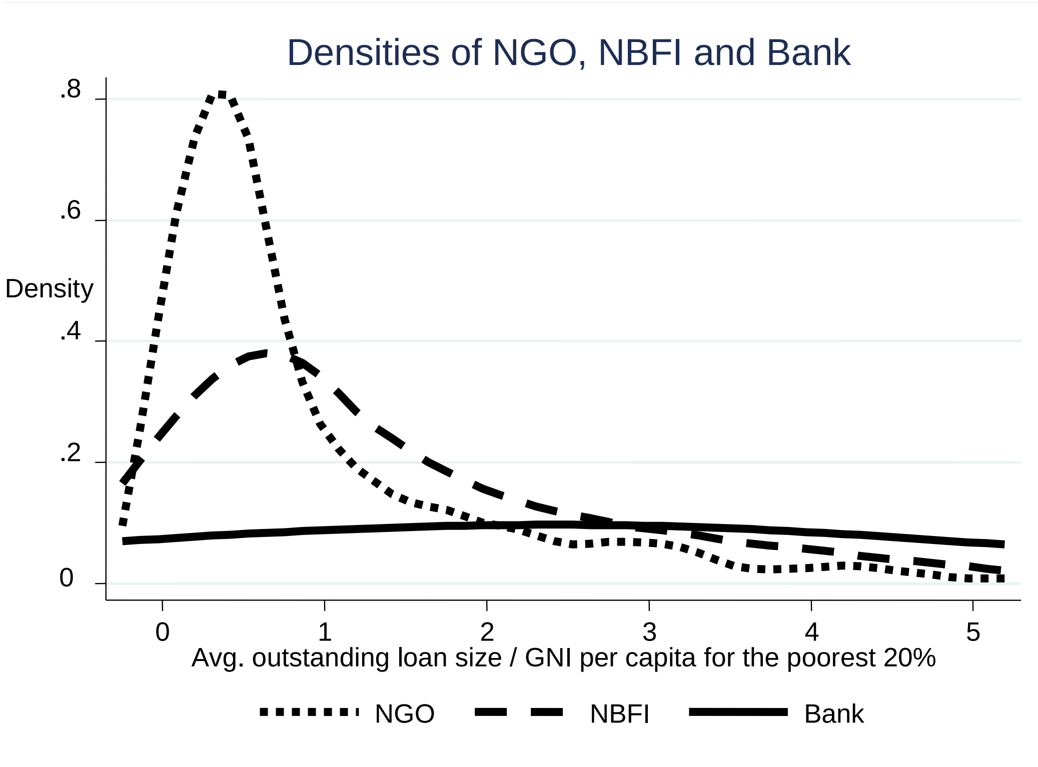


Figure 1: Density of microfinance institutions by institutional type

Original, underlying data provided by Microfinance Information eXchange, Inc. (MIX).

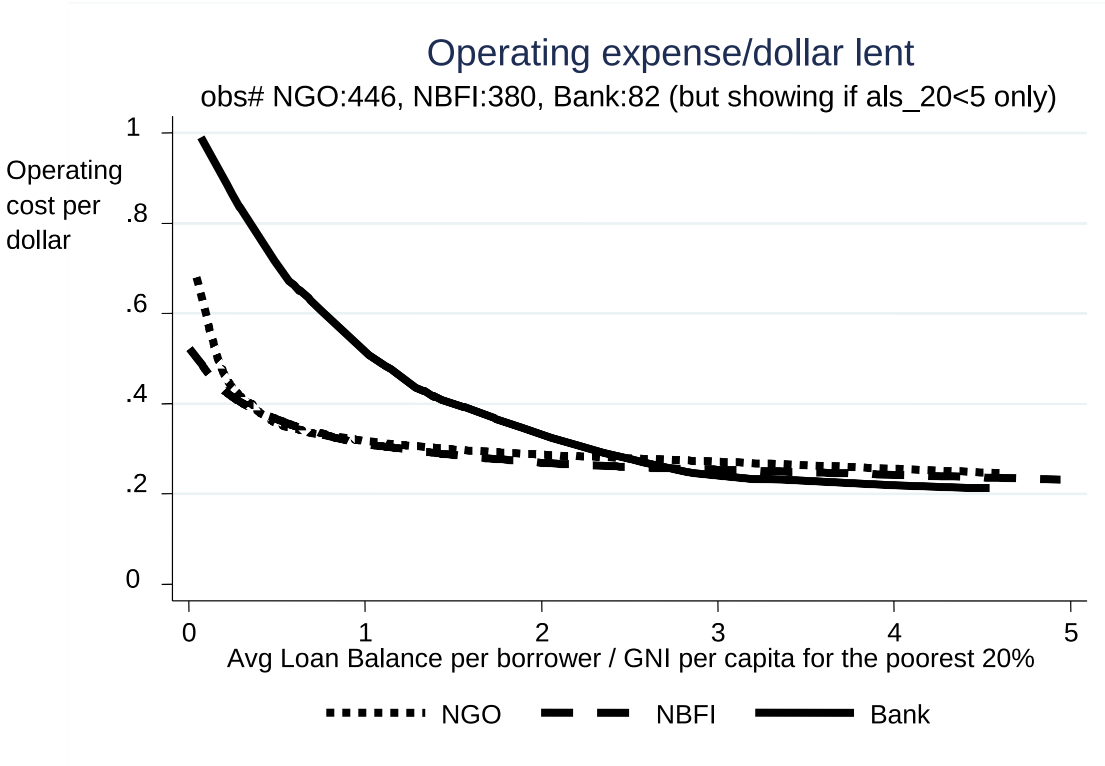


Figure 2: Operating expense per unit lent

Original, underlying data provided by Microfinance Information eXchange, Inc. (MIX).

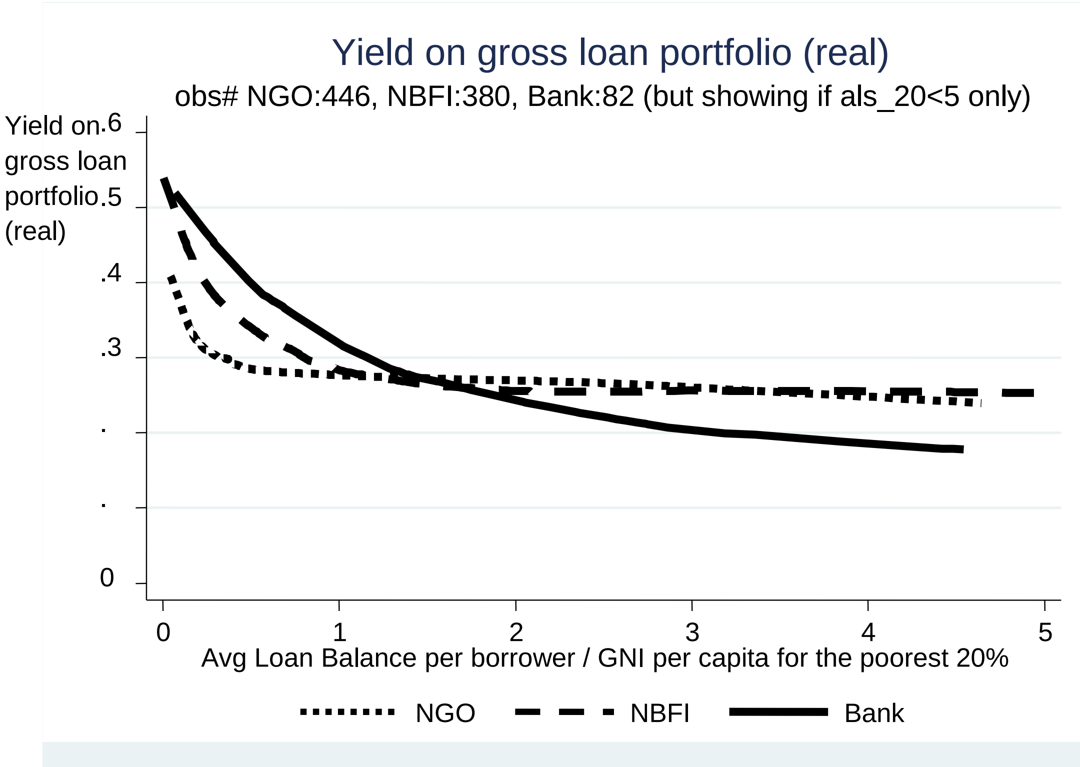


Figure 3: Average yield on gross portfolio (real)

Original, underlying data provided by Microfinance Information eXchange, Inc. (MIX).

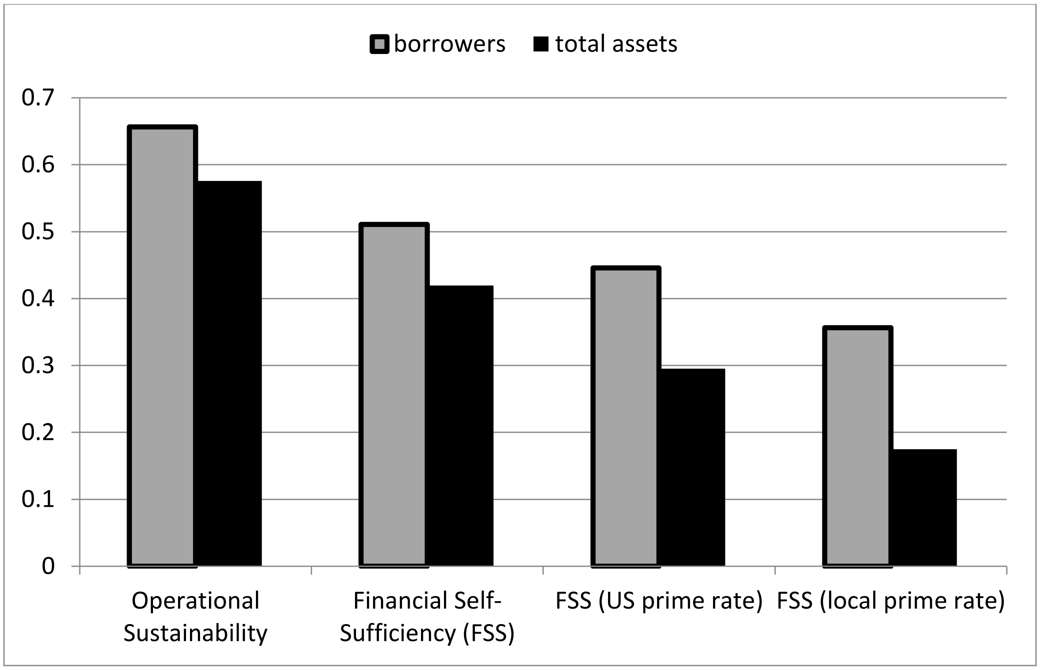


Figure 4: Percent of institutions that are profitable (FSS > 1) under different opportunity costs of capital

Original, underlying data provided by Microfinance Information eXchange, Inc. (MIX).

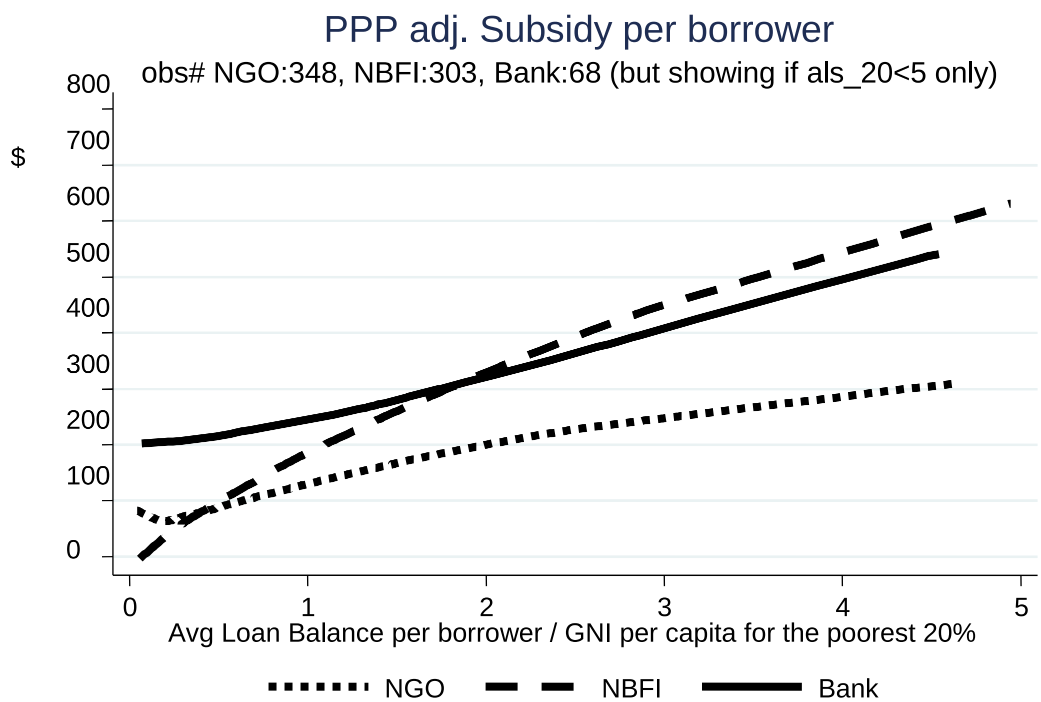


Figure 5: Subsidy per borrower: by institution, γ=local prime

Original, underlying data provided by Microfinance Information eXchange, Inc. (MIX).

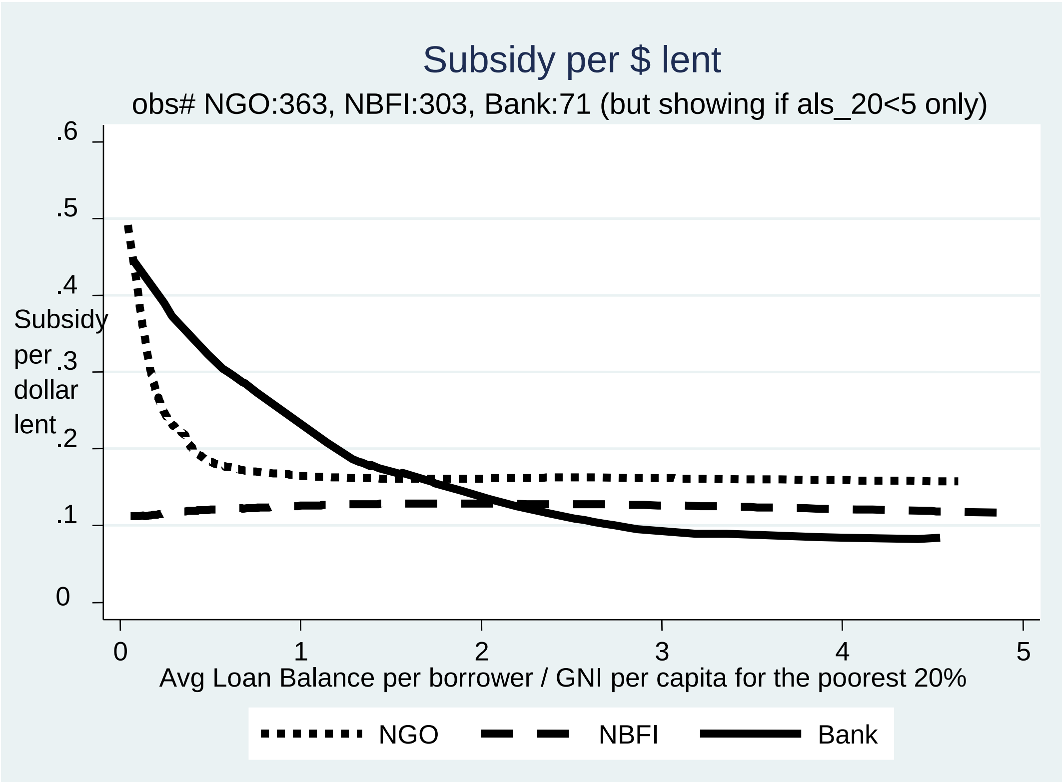


Figure 6: Subsidy: by institution
γ=local prime

Original, underlying data provided by Microfinance Information eXchange, Inc. (MIX).

Sample	Mean	25th percentile	Median	75th percentile	Observations
Full sample	2.4	0.4	1.0	2.5	1279
Bank (For-profit)	6.9	1.4	3.6	8.6	86
Credit union/ Cooperative (Not-for-profit)	2.9	0.7	1.7	3.7	232
NGO (Not-for-profit)	1.4	0.3	0.5	1.4	443
NBFI (For-profit)	2.8	0.4	1.1	2.6	293
NBFI (Not-for-profit)	2.4	0.7	1.2	2.6	92
Rural Bank	1.4	0.7	1.2	1.9	93
For-profit	3.2	0.5	1.3	2.8	479
Not-for-profit	2.0	0.3	0.9	2.3	790

Table 1. Average loan size divided by GNI per capita at the 20th percentile of the population, Most recent observation 2005-2009

Original, underlying data provided by Microfinance Information eXchange, Inc. (MIX).

Sample	Mean	25th percentile	Median	75th percentile	Obs
Full sample	25.0	13.7	20.7	33.1	1320
Bank (For-profit)	21.9	12.0	16.0	26.9	84
Credit union/ Cooperative (Not-for-profit)	17.9	10.9	16.1	22.1	234
NGO (Not-for-profit)	27.9	15.5	23.5	38.0	462
NBFI (For-profit)	28.3	14.9	24.1	37.9	298
NBFI (Not-for-profit)	24.9	16.8	24.2	33.1	98
Rural Bank	20.5	13.9	19.8	25.8	102
For-profit	26.1	14.1	21.4	34.0	491
Not-for-profit	24.3	13.5	20.2	32.5	819

Table 2. Real portfolio yield (percent), Most recent observation 2005-2009

Original, underlying data provided by Microfinance Information eXchange, Inc. (MIX).

Table 3: Portfolio Yield and Average Loan Size

Dependent variable			**Real portfolio yield (0.01=1%)**		
	1	2	3	4	5
Average Loan Size / GNI per capita poorest 20%	-0.0053***	-0.0102**	-0.0163***	-0.0139***	-0.0272***
	[0.004]	[0.033]	[0.000]	[0.001]	[0.000]
Sq. Average Loan Size / GNI per capita poorest 20%		0.0001	0.0002***	0.0002**	0.0005***
		[0.131]	[0.009]	[0.019]	[0.001]
Europe and Central Asia			-0.0814*	-0.1108**	-0.0902**
			[0.088]	[0.018]	[0.044]
East Asia and Pacific			-0.06	-0.0496	-0.0373
			[0.284]	[0.424]	[0.596]
Sub-Saharan Africa			-0.0446	-0.0639	-0.0489
			[0.371]	[0.195]	[0.329]
South Asia			-0.2145***	-0.2187***	-0.2340***
			[0.000]	[0.000]	[0.000]
Middle East & North Africa			-0.0599	-0.0745	-0.0854**
			[0.260]	[0.137]	[0.047]
Log of average total assets				-0.0074*	-0.0113***
				[0.075]	[0.003]
Age of MFI				-0.0031***	-0.0018***
				[0.000]	[0.003]
Bank (for-profit)					-0.0194
					[0.609]
Credit union, coop (Not-for-profit)					-0.1077***
					[0.002]
NGO (Not-for-profit)					0.005
					[0.865]
NBFI (For-profit)					0.0203
					[0.557]
Rural banks					-0.0262
					[0.571]
Bank (for-profit) * ALS for the poorest 20%					0.0196***
					[0.004]
Credit union, coop (Not-for-profit) * ALS for the poorest 20%					0.0151*
					[0.091]
NGO (Not-for-profit) * ALS for the poorest 20%					-0.0019
					[0.811]
NBFI (For-profit) * ALS for the poorest 20%					0.0116
					[0.149]
Rural banks * ALS for the poorest 20%					-0.0349
					[0.353]
Bank (for-profit) * Sq. ALS for the poorest 20%					-0.0004***
					[0.001]
Credit union, coop (Not-for-profit) * Sq. ALS for the poorest 20%					-0.0002
					[0.205]
NGO (Not-for-profit) * Sq. ALS for the poorest 20%					0
					[0.852]
NBFI (For-profit) * Sq. ALS for the poorest 20%					-0.0003**
					[0.035]
Rural banks * Sq. ALS for the poorest 20%					0.0027
					[0.732]
Constant	0.2604***	0.2687***	0.3471***	0.5080***	0.5721***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	1,261	1,261	1,261	1,243	1,243
R-squared	0.023	0.03	0.172	0.215	0.279
Adjusted R-squared	0.0222	0.029	0.168	0.209	0.265
Number of countries	91	91	91	91	91

Table 3 (continued): Portfolio Yield and Average Loan Size

Test, H0: ALS 20%+ALS 20%_Bank (profit)=0	**0.0618**
Test, H0: ALS 20%+ALS 20%_Coop (Not profit)=0	0.0405
Test, H0: ALS 20%+ALS 20%_NGO (Not profit)=0	0.000182
Test, H0: ALS 20%+ALS 20%_NBFI (profit)=0	0.0611
Test, H0: ALS 20%+ALS 20%_Rural bank=0	0.0944
OTest, H0: ALS 20%_sq+ALS 20%_sq_Bank (profit)=0	0.292
Test, H0: ALS 20%_sq+ALS 20%_sq_Coop (Not profit)=0	0.059
Test, H0: ALS 20%_sq+ALS 20%_sq_NGO (Not profit)=0	0.000469
Test, H0: ALS 20%_sq+ALS 20%_sq_NBFI (profit)=0	0.129
Test, H0: ALS 20%_sq+ALS 20%_sq_Rural bank=0	0.685

Notes. *, **, *** represent significance at the 10, 5, and 1 percent levels, respectively. The omitted category in model 5 is not-for-profit NBFIs. All models estimated using OLS with standard errors clustered at the country level. Original, underlying data provided by Microfinance Information eXchange, Inc. (MIX).

Sample	Mean	25th percentile	Median	75th percentile	Observations
Full sample	248	0	51	203	929
Bank (For-profit)	578	28	215	1097	67
Credit union/ Cooperative (Not-for-profit)	243	8	113	273	128
NGO (Not-for-profit)	174	5	51	146	345
NBFI (For-profit)	333	0	47	230	220
NBFI (Not-for-profit)	294	19	84	312	83
Rural Bank	18	0	0	0	59
For-profit	316	0	27	222	359
Not-for-profit	207	7	61	196	562

Note: Opportunity costs for equity capital (Prime) - Profit before tax + Adjusted in kind subsidy + Opportunity costs for loan capital (Prime - actual paid rate)

Table 4. PPP adjusted Subsidy per borrower, "Prime" adjustment for implicit equity subsidy. Most recent observations 2005-2009

Original, underlying data provided by Microfinance Information eXchange, Inc. (MIX).

Table 5: Subsidy per Borrower and Average Loan Size

Dependent variables	Subsidy per borrower (Local prime-actual paid rate)			
	1	2	3	4
Average Loan Size / GNI per capita poorest 20%	35.6559*	37.2541*	7.8046**	7.0342**
	[0.058]	[0.054]	[0.021]	[0.027]
Europe and Central Asia	115.7205	94.0187	155.4196**	173.4702**
	[0.154]	[0.258]	[0.035]	[0.018]
East Asia and Pacific	-68.1446	-70.9165	-37.669	-25.2122
	[0.168]	[0.129]	[0.461]	[0.635]
Sub-Saharan Africa	-87.0423	-101.0891	-75.2204	-72.2872
	[0.157]	[0.104]	[0.176]	[0.204]
South Asia	-54.4177	-56.6548	-31.1592	-32.5178
	[0.294]	[0.273]	[0.508]	[0.509]
Middle East & North Africa	-29.4527	-40.3954	1.3292	15.8682
	[0.570]	[0.449]	[0.981]	[0.789]
Log of average total assets		-14.1986	-21.4005***	-15.3363**
		[0.164]	[0.009]	[0.041]
Age of MFI		-1.8529*	-0.651	-1.1046
		[0.055]	[0.585]	[0.366]
Portfolio yield (nominal)				-377.7644**
				[0.011]
Capital costs assets ratio				-496.2402
				[0.166]
Operating costs assets ratio				434.2736**
				[0.015]
Bank (for-profit)			173.6384***	166.2569***
			[0.005]	[0.006]
Credit union, coop (Not-for-profit)			-73.7119	-48.7737
			[0.387]	[0.479]
NGO (Not-for-profit)			-40.2399	-51.8133
			[0.535]	[0.399]
NBFI (For-profit)			35.2031	35.463
			[0.582]	[0.559]
Rural banks			5.3074	40.0133
			[0.924]	[0.515]
Bank (for-profit) * ALS for the poorest 20%			4.9543	5.4469
			[0.566]	[0.530]
Credit union, coop (Not-for-profit) * ALS for the poorest 20%			21.8309	18.6408
			[0.175]	[0.197]
NGO (Not-for-profit) * ALS for the poorest 20%			69.0765**	70.6424**
			[0.041]	[0.039]
NBFI (For-profit) * ALS for the poorest 20%			31.8264	30.6471
			[0.173]	[0.179]
Rural banks * ALS for the poorest 20%			-4.0476	-17.9311**
			[0.546]	[0.044]
Constant	51.9273	303.2091*	381.9456**	362.3290**
	[0.344]	[0.065]	[0.013]	[0.022]
Observations	962	948	948	933
R-squared	0.21	0.218	0.313	0.342
r2_a	0.205	0.211	0.3	0.326
N_clust	75	75	75	75

Table 5 (continued): Subsidy per Borrower and Average Loan Size

Test, H0: ALS 20%+ALS 20%_Bank (profit)=0	**0.206**	**0.213**
Test, H0: ALS 20%+ALS 20%_Coop (Not profit)=0	0.0555	0.0589
Test, H0: ALS 20%+ALS 20%_NGO (Not profit)=0	0.0232	0.0242
Test, H0: ALS 20%+ALS 20%_NBFI (profit)=0	0.0893	0.0961
Test, H0: ALS 20%+ALS 20%_Rural bank=0	0.501	0.206

Notes. *, **, *** represent significance at the 10, 5, and 1 percent levels, respectively. The omitted category in models 3 and 4 is not-for-profit NBFIs. All models estimated using OLS with standard errors clustered at the country level. Original, underlying data provided by Microfinance Information eXchange, Inc. (MIX).

MFI Type	Obs.	% with subsidy=0	MFIs with Subsidy > 0							
			Obs.	Average Shares			Median Shares			Profits/ Subsidy (median)
				Donated equity	Subsidized borrowing	Other donations (in-kind)	Donated equity	Subsidized borrowing	Other donations (in-kind)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Full sample	1024	14.5	876	23.8	74.8	1.3	0.1	99.6	0.0	62%
Bank (For-profit)	73	17.8	60	2.8	96.6	0.6	0	100.0	0.0	54%
Credit union/ Cooperative (Not-for-profit)	160	17.5	132	27.1	70.8	2.1	8.2	91.1	0.0	121%
NGO (Not-for-profit)	377	4.8	359	32.5	66.5	1.0	13.6	84.9	0.0	42%
NBFI (For-profit)	226	17.7	186	10.4	87.5	2.2	0	100.0	0.0	68%
NBFI (Not-for-profit)	92	4.3	88	30.3	69.6	0.1	10.5	89.5	0.0	61%
Rural Bank	67	53.7	31	3.2	93.6	3.1	0	100.0	0.0	1313%
For-profit	379	24.3	287	8.8	89.3	1.9	0	100.0	0.0	82%
Not-for-profit	637	8.0	586	31.1	67.8	1.1	12.6	86.4	0.0	51%

Table 6. Breakdown of subsidy by MFI Type

Notes: Figures include all MFIs for which we can calculate our subsidy measure. The number of observations is higher than in the Subsidy/borrower calculations shown in Table 4 because (a) we lack information on the number of borrowers for 22 MFIs for which we can calculate subsidy and (b) we are unable to PPP-adjust for an additional 73 MFIs.

TABLE 7. Benefit-Cost Ratios, Various Development Interventions

Microcredit

Study	Country	Horizon: Time from baseline to endline survey	Beneficiaries	Δ Monthly Income	Loan Size	Benefit-Cost Subsidy (Cost) is 7.6% of loan size	Benefit-Cost Subsidy (Cost) is median for NGOs in our sample
Angelucci et al. (2015)	Mexico	16-20 mos.	Groups (10-50); Predominantly women	-7 pesos	6462 pesos	-0.01	-0.02
Attanasio et al. (2015)	Mongolia	~1.5 years after microcredit introduced	Groups (7-15 women)	24,761 togrog	954,860 togrog	0.34	0.37
Augsburg et al. (2015)	Bosnia Herzegovina	~14 months	Individuals	33 BAM	1653 BAM	0.15	0.51
Banerjee et al. (2015)	India	~2 years (2 50-week loan cycles)	6-10 women per group	401 Rps	20000 Rps. (2 loans)	0.26	0.19
Crépon et al. (2015)	Morocco	2 years	Groups (3-4)	94 MAD	8000 MAD	0.15	0.49
Tarozzi et al. (2015)	Ethiopia	2+ years after microcredit introduced	Groups (5-7)	48 Birr	1200 Birr	0.53	0.25

Grants to Ultra-poor

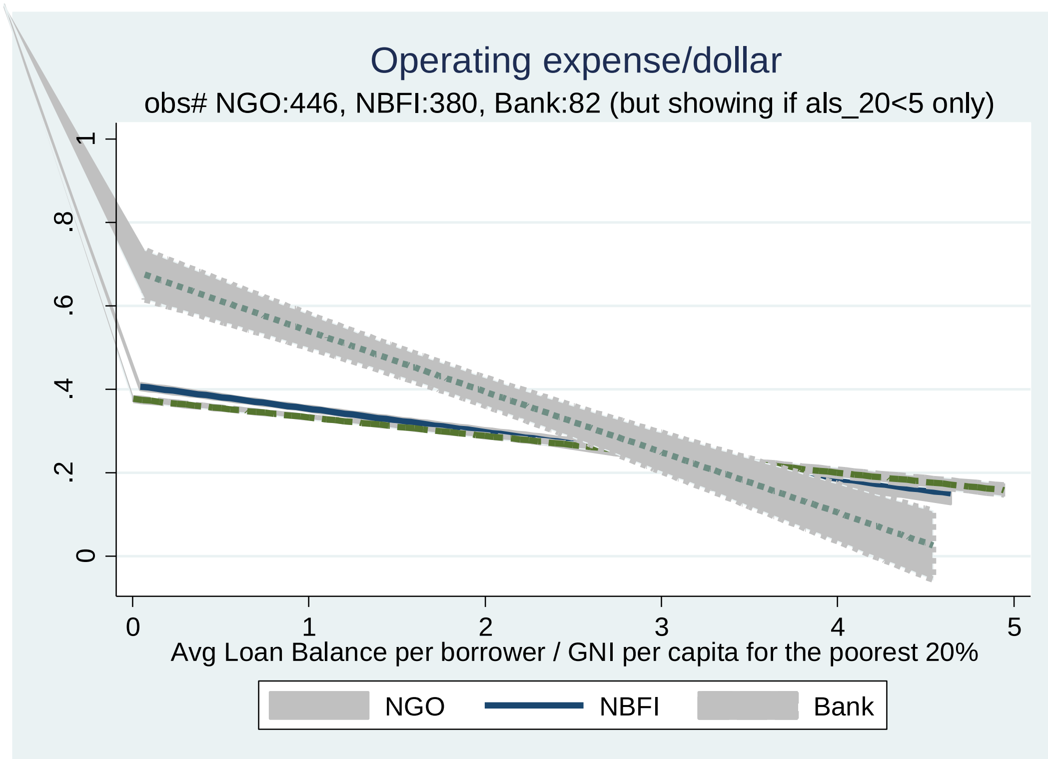
Study	Countries	Time Horizon	Δ Consumption	Cost	Benefit-Cost (Avg)	Benefit-Cost (Range)
Bandiera et al., (2016)	Bangladesh	4 years	1118	1363	0.82 (Assuming benefits last 5 years)	Benefits in perpetuity 5.40 Benefits last 10 years 1.86
Banerjee et al. (2015)	Ethiopia, Ghana, Honduras, India, Pakistan, Peru	3 years	[-$6118, $10,875]	[$1,455-$5,962]		Benefits in perpetuity [-1.98-4.33]
Blattman et al. (2016)	Uganda	~3 years			~5.0[a] (Benefits in Perpetuity)	

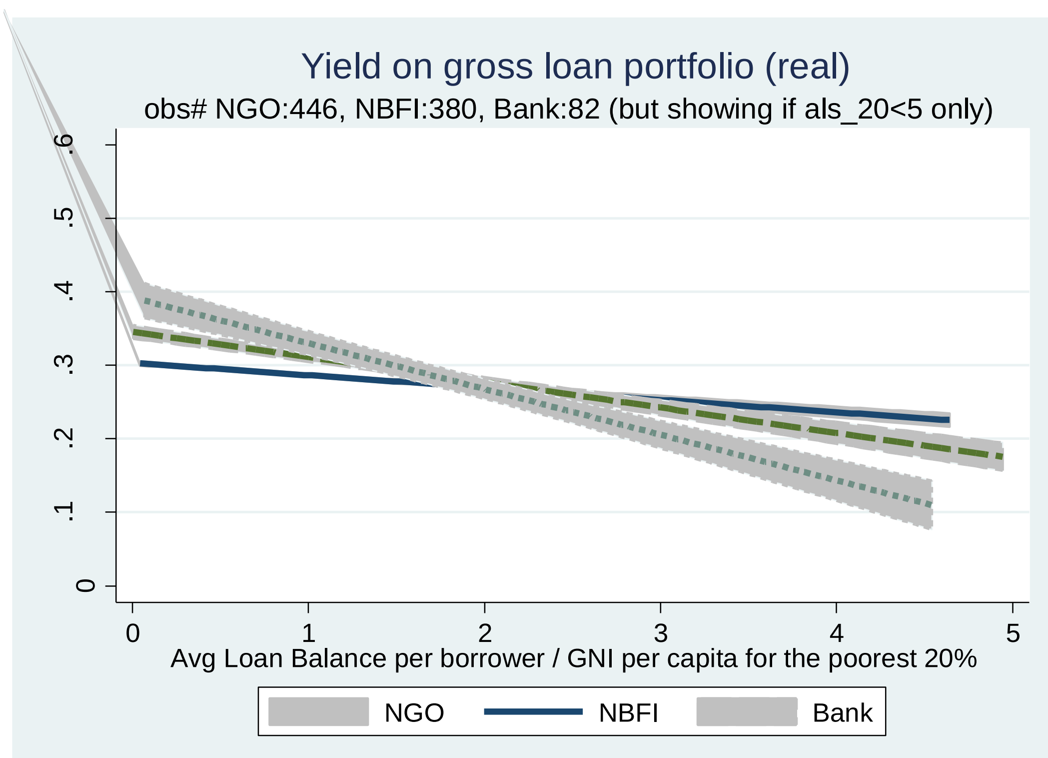
Vocational Training

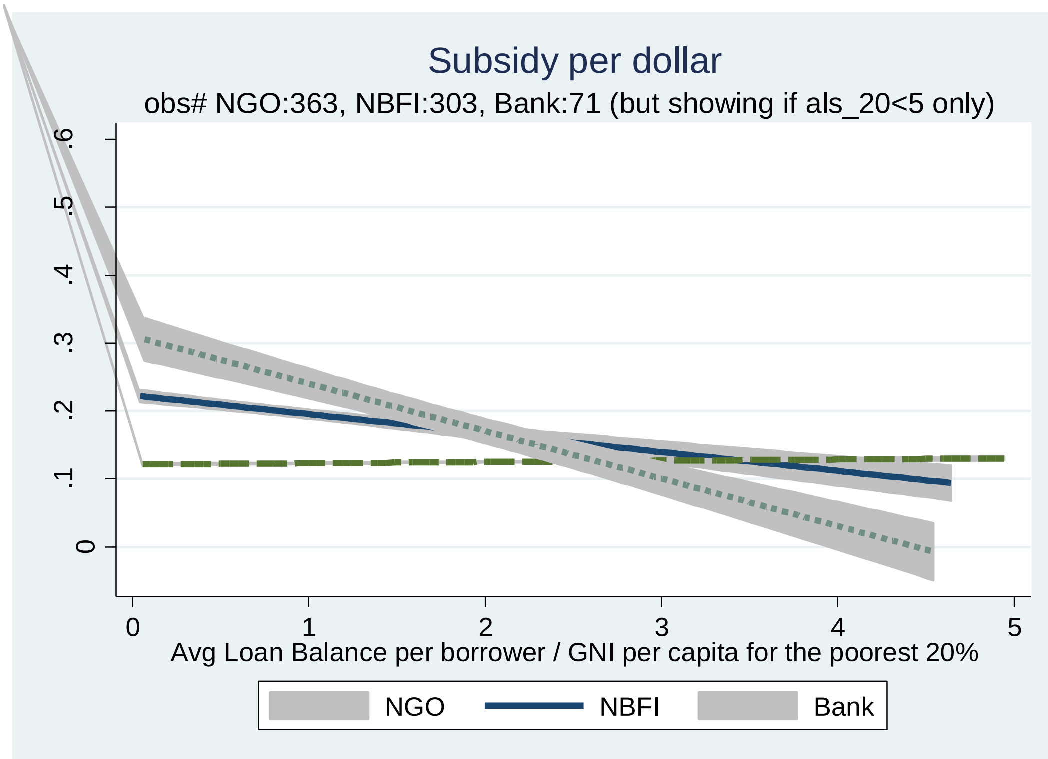
Study	Countries	Time Horizon	Δ Monthly Income	Cost	Benefit-Cost (Avg)	Benefit-Cost (Range)
McKenzie (2017)	Argentina, Colombia, Dominican Rep., India, Kenya, Turkey	12-24 mos.	$2.40 - $83	$13 - $1722	0.05	[0.01-0.18]

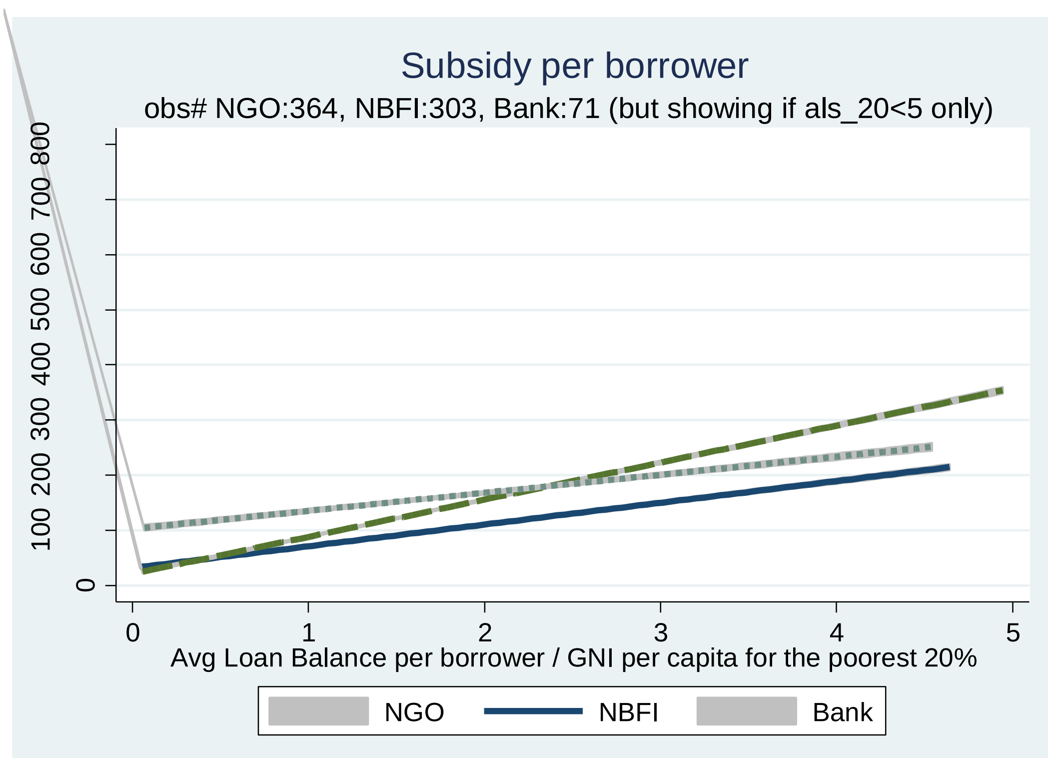
Notes. Microcredit: All estimates of changes in income from the six microcredit studies come from the respective Table 4s, and are reported in local currency. Income change converted to monthly for those studies reporting changes in annual income. In column (7) subsidy is calculated as 7.6% of loan size, since the median subsidy for NGOs in our sample is 7.6 cents per dollar lent. In column (8), we use the median subsidy per borrower for NGO MFIs ($26) converted to local currency. Change in income in Benerjee et al. (2015) is measured after baseline 2.
Grants to Ultra-Poor: [a] Blattman et al. (2014) find that earnings among young self-employed Ugandans increased by 30-50% of the size of the grant for a similar program, but do not explicitly calculate a benefit-cost ratio.

Appendix A.


Operating expense/dollar
obs# NGO:446, NBFI:380, Bank:82 (but showing if als_20<5 only)
0
.2
.4
.6
.8
1
0
1
2
3
4
5
Avg Loan Balance per borrower / GNI per capita for the poorest 20%
NGO
NBFI
Bank


Yield on gross loan portfolio (real)
obs# NGO:446, NBFI:380, Bank:82 (but showing if als_20<5 only)
0
.1
.2
.3
.4
.5
.6
0
1
2
3
4
5
Avg Loan Balance per borrower / GNI per capita for the poorest 20%
NGO
NBFI
Bank


Subsidy per dollar
obs# NGO:363, NBFI:303, Bank:71 (but showing if als_20<5 only)
0
.1
.2
.3
.4
.5
.6
0
1
2
3
4
5
Avg Loan Balance per borrower / GNI per capita for the poorest 20%
NGO
NBFI
Bank


Subsidy per borrower
obs# NGO:364, NBFI:303, Bank:71 (but showing if als_20<5 only)
0
100
200
300
400
500
600
700
800
0
1
2
3
4
5
Avg Loan Balance per borrower / GNI per capita for the poorest 20%
NGO
NBFI
Bank

Online Technical Appendix

Part A. Financial self-Sufficiency Calculations

The MIX Market presents a calculation of profitability: i.e., the financial self-sufficiency (FSS) ratio. This notion of financial self-sufficiency is meant to indicate whether an organization can continue operations without external donor funding, but the FSS ratio falls short of accounting for inputs at their opportunity costs. The MIX Market reports that they make a cost-of-funds adjustment to account for the impact of "soft loans." The MIX Market calculates "the difference between what the MFI actually paid in interest on its subsidized liabilities and what it would have paid at market terms." To do that, the MIX Market uses data for shadow interest rates from the IMF's *International Financial Statistics* database, using the country's deposit rate as the benchmark.[47]

Yaron (1994) and Shreiner and Yaron (2001) argue that this adjustment is inadequate and that the FSS thus over-states financial self-sufficiency. The deposit rate provides a benchmark for the cost of borrowing by microfinance banks that is too low: The interest rate spread (the difference between the interest rate charged by banks to private sector customers when lending and the interest rate that the private sector offers to its depositors) is generally over 5 percentage points. (2014 World Bank data, for example, show that the interest rate spread for low income countries as a group was 11.2 percentage points and 6.4 percentage points for middle income countries as a whole.)[48] Moreover, many institutions, are not legally able to collect deposits, and even those that are able to do so face transactions costs associated with deposit collection. In addition, the

---

[47] From MIX Market, "Benchmarks Methodology" http://www.themix.org/sites/default/files/Methodology%20for%20Benchmarks%20and%20Trendlines.pdf.

[48] The 2014 World Bank *World Development Indicators* Table 5.5 (http://wdi.worldbank.org/table/5.5).

FSS calculation implicitly (and implausibly) assumes that an institution's equity-holders seek no real return to their investments.

The definition of economic profit is closely related to the subsidy dependence index (SDI) developed by Yaron (1994) and explored further by Schreiner and Yaron (2001) and Manos and Yaron (2009). But rather than calculate an index, we focus on the distribution of subsidy in the context of the microfinance business model. Key variables include:

Financial Self-sufficiency ratio. The formula that the MIX Market uses to calculate the Financial Self-sufficiency ratio (FSS) is:

> Financial revenue / [Financial expense + Operating expense + Net loan loss + Net inflation adjustment + MIX subsidy adjustment].

The MIX subsidy adjustment uses the IMF deposit rate as the alternative cost of capital:

> MIX subsidy adjustment = total borrowing * deposit rate - interest expense on total borrowings.

If the interest expense actually paid by the microfinance institution exceeds the expense it would incur when borrowing at the deposit rate, the MIX subsidy adjustment is set to zero.

Economic profit. The calculation we use differs in two ways. First, we replace the deposit rate with the country's prime lending interest rate (taken from the World Bank's *World Development Indicators*). For comparison, we also use the US prime interest rate in some calculations.[49] We thus replace the MIX subsidy adjustment with:

> Subsidy adjustment = total borrowing * (prime lending rate) - interest expense on total borrowings.

[49] Where the interest rate is not available in the *World Development Indicators*, we use data from country publications. For example, we take India's rates from the Indian government statistics website (Chapter 24 "Banks, Table 24 Money rates in India"). Available at: http://mospi.nic.in/Mospi_New/site/India_Statistics.aspx?status=1&menu_id=14 ".

Second, we add an adjustment for implicit subsidies to equity:

Equity adjustment = Total donated equity amount * (prime lending rate)

This gives us a formula for financial self-sufficiency that reflects economic profit:

Financial Self-Sufficiency = Financial revenue / [Financial expense + Operating expense + Net loan loss + Net inflation adjustment + Subsidy adjustment + Equity Adjustment].

Part B. Subsidies Calculated Using Official Exchange Rates

Sample	Mean	25th percentile	Median	75th percentile	Observations
Full sample	132	0	26	102	1002
Bank (For-profit)	275	20	93	417	72
Credit union/ Cooperative (Not-for-profit)	110	9	46	117	159
NGO (Not-for-profit)	101	3	23	75	371
NBFI (For-profit)	201	0	22	117	221
NBFI (Not-for-profit)	133	10	51	147	92
Rural Bank	9	0	0	0	59
For-profit	178	0	14	107	365
Not-for-profit	108	4	32	98	629

Note: Opportunity costs for equity capital (Prime) - Profit before tax + Adjusted in kind subsidy + Opportunity costs for loan capital (Prime - actual paid rate)

Table 4a. Subsidy per borrower, "Prime" adjustment for implicit equity subsidy.
Most recent observations 2005-2009

Original, underlying data provided by Microfinance Information eXchange, Inc. (MIX).