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Financing new entrepreneurship: Credit or microcredit?

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ABSTRACT

Building on the theory of information asymmetry, we investigate the impact of conventional banking versus the impact of microfinance on new entrepreneurship. We use a panel dataset collected from 49 developing countries between 2003 and 2018 and apply a random effects linear regression model with endogenous sample selection. We show, among other results, that conventional banking has no direct impact on new entrepreneurship. In contrast to conventional banking, microfinance appears to promote the growth of new entrepreneurship. However, as the conventional banking sector grows, the positive impact of microfinance on new entrepreneurship diminishes.

1. Introduction

The second most cited obstacle to the growth of microenterprises in developing countries is access to finance. The lack of employment history, credit history, and collateral are central barriers in preventing the access of new entrepreneurs to conventional banking. Following the potential scenarios of adverse selection and moral hazard, microfinance institutions (MFIs) have developed alternative techniques to overcome information asymmetry and manage the risk of providing small loans (microcredit) to new entrepreneurs (Ahlin, 2020). This study is the first to evaluate the impact of conventional banking and the impact of microfinance on new entrepreneurship, which is generally defined as the creation of new small businesses (Gartner, 1985).

Microfinance is composed of techniques designed to ease the barriers that conventional banks face in serving "unbankable" borrowers, such as joint liability group lending, regular repayment schedules, and dynamic incentives. First, individuals in group lending self-select each other in a group and are held liable for each other's loans. Group lending includes peer selection, peer monitoring, peer pressure, and mutual insurance. The social capital inherent in group lending replaces the physical collateral and mitigates the impact of information asymmetry. Second, weekly/biweekly repayments in small amounts force borrowers to save and ensure smooth repayment. Third, borrowers in dynamic incentives are entitled to future larger loans following the timely repayment of their current loans. Dynamic incentives can reduce ex-ante and ex-post moral hazard. These techniques, among others, form a lending model that tackles information asymmetry and enables top MFIs in achieving repayment rates of 98% and higher (Cull et al., 2009).

The majority of the studies that evaluate the impact of microfinance on new entrepreneurship are based on randomized controlled trials conducted in small areas with the cooperation of some MFIs (Duvendack and Mader, 2019; Bika et al., 2022). In a randomized evaluation of a group-lending program operating in 52 randomly selected neighborhoods in Hyderabad, Banerjee et al. (2015) showed that the program increases the investments and profits of small businesses. In contrast, using randomized controlled trials, Karlan and Zinman (2011) found no impact of an individual-based lending program on small businesses in Manila. Bika et al. (2022) and several other meta-studies (Duvendack and Mader, 2019) concluded that microcredit has inconclusive effects on entrepreneurship.

New entrepreneurs in developing countries are likely to be motivated by necessity (Margolis, 2014). Unlike opportunity entrepreneurs, necessity entrepreneurs comprise individuals who are unemployed at the time they started a business. Because of their lack of credit history and appropriate collateral, new entrepreneurs are likely to be considered as high risk and thus less likely to obtain bank loans. However, MFIs have designed specific techniques to minimize the risk of funding new entrepreneurs. We test the following hypotheses accordingly:

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H1: *Conventional banking has no impact on new entrepreneurship.*
H2: *Microfinance has a positive impact on new entrepreneurship.*

Unlike the literature that involves small regions in certain countries, we use cross-country panel dataset and consider sample selection concerns. The empirical results of this study are in favor of the aforementioned hypotheses. Moreover, we find that the growth of conventional banking discourages the positive impact of microfinance on new entrepreneurship.

2. Data and variables

We combine data on the state of microfinance, entrepreneurship, macroeconomic, and institutional conditions from the Microfinance Information Exchange (MIX) Market,[1] the Global Entrepreneurship Monitor (GEM),[2] and the World Bank. GEM comprises 22 years of data of 115 countries gathered from approximately 200,000 interviews with experts and entrepreneurs. It uses a sample of approximately 2000 adults in each country, ensuring that all geographic regions, urban and rural, are representative. GEM surveys a representative sample of each country's population to determine the percentage involved in total early-stage entrepreneurial activities (*TEA*) and fear of failure rate (*FEAR*), among other variables. *TEA* is our proxy for new entrepreneurship defined as the percentage of the 18–64 population either actively planning a new business (nascent) or owning/managing a new business that is 3.5 years old or less.[3] *FEAR* is the percentage of the 18–64 population that indicates that fear of failure would prevent them from setting a business.[4]

MIX provides financial, operational, and social performance data on over 3000 MFIs targeting "unbanked" individuals and small businesses in more than 100 developing countries in both rural and urban regions. Parmeter and Hartarska (2021) highlighted the salient features of MIX Market data. Our proxy for the impact of microfinance is the total gross loan portfolio of the MFIs as a percentage of the country's GDP (*MICROCREDIT*). The total number of MFIs used to extract *MICROCREDIT* is 1905 as observed in 49 countries out of 109 used in the dataset. Because reporting to the MIX Market is voluntary, the observed *MICROCREDIT* will be smaller than its true value. However, a study by Bauchet and Morduch (2010) concluded that the MIX Market database comprises a set of medium-to large-sized MFIs and that the patterns of reporting align with the size of the MFIs. Therefore, larger MFIs are more likely to report to the MIX Market than smaller ones, giving *MICROCREDIT* some validity to measure the overall size of the microfinance sector.

We use domestic credit to private sector by banks as a percentage of GDP (*CREDIT*) to test the first hypothesis. We control for the macroeconomic and institutional conditions of the growth of GDP (*GROWTH*), unemployment rate (*UNEMPLOY*), percentage of tertiary education (*EDUC*), and simple average of the World Governance Indicators (*GOVERNANCE*).

This study uses unbalanced panel data spanning the period from 2003 to 2018. Following the microfinance literature, we drop the lowest and highest 2.5% of the values of *MICROCREDIT*. The summary statistics is given in Table 1. Although domestic credit makes approximately 40% of a country's GDP, microcredit makes a tiny fraction of it. Figs. 1 and 2 show the scatter diagrams of the mean of *TEA* and the means of *CREDIT* and *MICROCREDIT* collapsed at the country level.

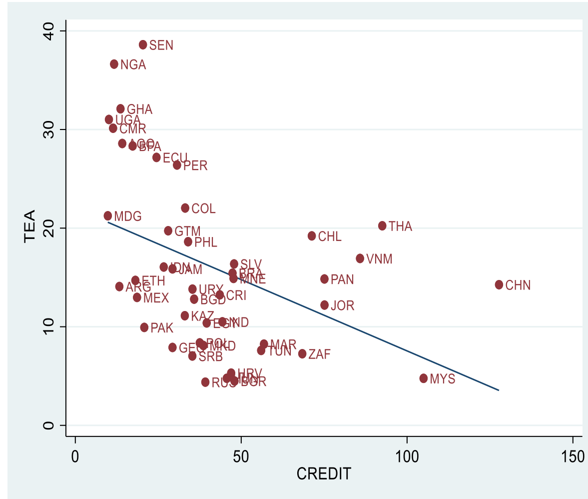

Fig. 1. Domestic credit and TEA.

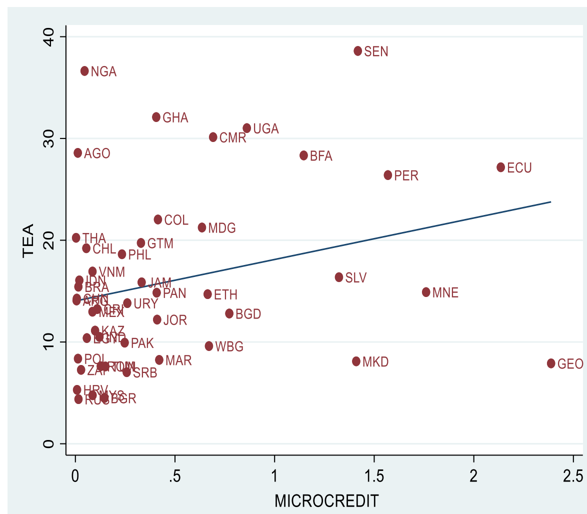

Fig. 2. Microcredit and TEA.

3. Methodology

We fit a panel data random effects model with endogenous sample selection and within-panel correlation. *TEA* is modeled as

$$\ln(TEA_{it}) = \boldsymbol{x}_{it}\beta + \upsilon_{1i} + \varepsilon_{1it},$$

where x_{it} refers to the financing means of *CREDIT* or/and *MICROCREDIT* and a set of control variables, such as *GROWTH*, *UNEMPLOY*, *EDUC*, *GOVERNANCE*, *COUNTRY*, and *YEAR*. The terms υ_{1i} and ε_{1it} are the panel-level random effect and the observation-level error, respectively. The selection of countries by GEM is modeled

[1] The World Bank now hosts the MIX data.

[2] https://www.gemconsortium.org/data.

[3] We used the World Bank measure of entrepreneurship defined as the number of new limited liability corporations registered in a calendar year (New Registered Businesses). However, this measure is not suitable to test the hypotheses of this study for two main reasons. First, New Registered Businesses reflect formal entrepreneurship only. In contrast, TEA is more comprehensive and reflects both formal and informal entrepreneurship (Thai and Turkina, 2014). Second, the establishment of limited liability corporations in many countries requires a minimum capital that well exceeds the loan sizes provided by typical MFIs. Limited liability corporations are unlikely to be part of the MFIs target market.

[4] Individuals involved in entrepreneurial activities are excluded.

Table 1
Descriptive statistics.

Variable	Obs.	Mean	SD	Median	25th Percentile	75th Percentile
TEA	369	15.489	8.687	14.100	9.100	20.700
CREDIT	777	39.564	26.864	32.324	18.859	51.882
MICROCREDIT	1541	0.855	0.0140	0.275	0.051	1.007
FEAR	368	31.990	9.813	30.80	25.85	36.600
GROWTH	1582	5.263	2.978	4.949	3.213	6.890
UNEMPLOY	1738	7.752	6.257	5.860	3.500	10.140
EDUC	1112	28.157	21.738	24.314	9.195	43.116
GOVERNANCE	1684	−0.438	0.764	−0.489	−0.836	−0.151
GDPPERCAPITA	1740	3.619	3.971	2.329	0.904	4.979

as

$$SELECTION_{it} = 1(\boldsymbol{z}_{it}\alpha + \upsilon_{2i} + \varepsilon_{2it} > 0),$$

where $SELECTION_{it} = 1$ if TEA_{it} is observed and 0 otherwise. The term $\boldsymbol{z_{it}}$ is a set of variables explaining the selection, and the terms υ_{2i} and ε_{2it} are the panel-level random effect and the observation-level error, respectively. We use maximum likelihood to estimate the *TEA* and *SELECTION* equations. The variable *TEA* is not available for most countries, and this may not be random. The unobserved factors affecting *TEA* can be related to the unobserved factors affecting the selection of countries, which leads to an endogenously selected sample. We use GDP per capita measured in thousands of USD (*GDPPERCAPITA*), *GOVERNANCE*, *COUNTRY*, and *YEAR* to model the selection process. GEM is more likely to collect data from richer countries with better governance.

4. Empirical results and discussion

The estimation is based on the Heckman selection model (Heckman, 1979) for panel data available in Stata 16 ''*xtheckman*''. Table 2 shows the regression results. Standard errors are in parentheses, and ***, **, and * indicate 1%, 5%, and 10% significance levels. The first two panels show the estimated coefficients for the *TEA* and the *SELECTION* equations. The results suggest that conventional banks avoid including new entrepreneurs in their financial services. Banks may find it risky and costly to ensure the creditworthiness of the new entrepreneurs who usually require small loans. Monitoring and servicing small loans are more difficult and exorbitant relative to larger loans. The results validate the second hypothesis. MFIs' lending techniques seem to enhance the effectiveness of screening potential borrowers and monitoring their actions both necessary for the inclusion of new entrepreneurs. Interestingly, the coefficient on the interaction term suggests that the positive impact of microfinance fades away as conventional banking expands. The expansion of conventional banks may lessen microfinance and consequently reduce new entrepreneurship. In our sample, the correlation between *MICROCREDIT* and *CREDIT* is (−0.11).

The aforementioned results assume that the locations of the survey respondents in the GEM data are close to the locations of the MFIs. If not, the relationship between *MICROCREDIT* and *TEA* could only be associative. Data between the geographical proximity of the business activities and the MFIs are not available. However, given the methodology of collecting data by GEM, the dispersion of MFIs between rural and urban areas, and the presumably inelastic demand for microcredit (Karlan and Zinman, 2008), the access of new entrepreneurs to microcredit is likely to be a rule more than an exception (Imai et al., 2010), and the relationship between *MICROCREDIT* and *TEA* is likely to be more than just associative.

As expected, the results suggest that fear of failure inhibits new entrepreneurship. Although we find no impact of economic growth and governance on new entrepreneurship, unemployment seems to reduce new entrepreneurship. Intuitively, higher unemployment is expected to increase new entrepreneurial activities; however, the results favor a counter argument in that an increase in unemployment may ignite an overall pessimism about business conditions, which weakens the growth of entrepreneurship. The overall results suggest that education reduces new entrepreneurship. Although education increases the endowment of the entrepreneurs' human capital, educated people may prefer a wage work because of the prospects of stable earnings over the anxiety of business failure. The third panel in Table 2 shows the correlation of the observation-level residuals in the *TEA* and *SELECTION* equations (ε_{1it} and ε_{2it}) and the correlation of the random effects (υ_{1i} and υ_{2i}), respectively. Both correlations are statistically insignificant, which indicates that endogenous selection does not consist a problem. Estimates from pooled ordinary least squares, fixed effects, random effects, and system GMM models are consistent with the aforementioned findings.

Three key areas could further improve this study's findings. First, *TEA* is collected from a survey data, and measurement errors cannot be ruled out. Measurement errors in the dependent variable reduce precision due to higher standard errors; however, the estimates are unbiased (Millimet and Parmeter, 2022). Identifying an alternative measure for *TEA* will be an important addition to the findings of this study. Second, since reporting to the MIX Market is voluntary, *MICROCREDIT* will be smaller than its true value and will be subject to nonclassical measurement errors. As a result, the point estimates are vulnerable to bias and inconsistency. Correcting for potential nonclassical measurement error in *MICROCREDIT* remains another valuable extension to this study. Third, identifying the locations of the MFIs relative to the locations of the business activities can contribute toward establishing one of the pillars of causality between *MICROCREDIT* and *TEA*.

5. Conclusion

Because of their lack of credit history and appropriate collateral, new entrepreneurs in developing countries are likely to be evaluated as high risk and have little access to conventional banking. Conversely, microfinance developed alternative techniques that help in reducing information asymmetry. Using a rich dataset and accounting for selection bias, the empirical evidence of this study suggests that microfinance fosters new entrepreneurship, whereas conventional banking has no direct impact. However, a larger banking sector seemingly reduces the size of the microfinance sector and the positive impact of microfinance on new entrepreneurship. Governments, socially oriented organizations, and donors should adopt the right measures in facilitating the growth of microfinance, a tool for the growth of entrepreneurship and poverty alleviation.

Table 2
Random effects regressions with selection.

Panel A	$Ln\,(TEA_{it})$			
CONSTANT	3.3306***(0.2548)	3.3492*** (0.2836)	3.2252*** (0.2953)	3.1138*** (0.2610)
$CREDIT_{it}$	−0.0013(0.0023)		−0.0017 (0.0022)	−0.0002 (0.0022)
$MICROCREDIT_{it}$		0.1282*** (0.0493)	0.1512*** (0.0489)	0.4062*** (0.1370)
$CREDIT_{it} * MICROCREDIT_{it}$				−0.0051** (0.0025)
$FEAR_{it}$	−0.0099*** (0.0028)	−0.0104*** (0.0027)	−0.0096*** (0.0028)	−0.0095*** (0.0027)
$GROWTH_{it}$	0.0006 (0.0127)	−0.0076 (0.0120)	0.0029 (0.0125)	0.0042 (0.0125)
$UNEMPLOY_{it}$	−0.0321*** (0.0092)	−0.0305*** (0.0086)	−0.0352*** (0.0088)	−0.0331*** (0.0089)
$EDUC_{it}$	−0.0048 (0.0030)	−0.0091*** (0.0026)	−0.0053* (0.0028)	−0.0041 (0.0029)
$GOVERNANCE_{it}$	−0.2327 (0.1473)	−0.1066 (0.1441)	−0.1538 (0.1609)	−0.1698 (0.1403)
YEAR	Yes	Yes	Yes	Yes
COUNTRY	Yes	Yes	Yes	Yes
Panel B	$SELECTION_{it}$			
CONSTANT	−2.6205*** (0.4204)	−2.3348*** (0.3386)	−2.5261*** (0.3980)	−2.5757*** (0.4140)
$GDPPERCAPITA_{it}$	0.2356*** (0.0472)	0.2137*** (0.0400)	0.2293*** (0.0447)	0.2306*** (0.0464)
$GOVERNANCE_{it}$	0.3805** (0.1925)	0.3510** (0.1745)	0.3664* (0.1913)	0.3841** (0.1926)
YEAR	Yes	Yes	Yes	Yes
COUNTRY	Yes	Yes	Yes	Yes
Panel C				
$Corr(e.SELECTION, e.TAE)$	0.2438 (0.2499)	0.1796 (0.3049)	0.2053 (0.2983)	0.2058 (0.2817)
$Corr(SELECTION, TAE)$	0.0798 (0.2182)	0.3326 (0.4144)	0.3030 (0.4603)	0.1183 (0.2465)
Number of Observations	1,517	1,526	1,514	1,514
Selected	215	224	212	212
Non-selected	1,302	1,302	1,302	1,302
Number of Countries	109	109	109	109
Log Likelihood	−423.3934	−446.4234	−412.9530	−411.1286

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