**Microfinance and Poverty: A Country-level Panel Data Analysis**

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**Abstract.** The subject of this paper is microfinance—the expansion of loans to poor and low-income clients—and whether or not it has any impact on a country’s poverty level. In the past several decades microfinance has gained popularity among policymakers and other stakeholders and there have been concerted efforts to expand microfinance programs with the objective of promoting development and reducing poverty. However studies of the effect of microfinance on poverty have produced mixed results, and the number of studies of the effect on poverty at a macro level is limited. This study tests the hypothesis that countries with higher Microfinance Institutions’ (MFIs’) gross loan portfolio (GLP) per capita have lower levels of poverty using panel data covering approximately 70 developing countries for the years 1999-2014.

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# 1. Introduction

Microfinance, which emerged as an experiment conducted by a single economist in lending to poor households in a village in Bangladesh in the mid 1970’s, has evolved into a global movement impacting more than 200 million people (Beatriz and Morduch, 2010; Microcredit Summit Campaign, 2015). Microfinance can be broadly defined as the extension of loans and a broad range of other financial services to poor and low-income clients/communities that generally do not have access to traditional banking (Perossa and Marinaro, 2015; Buera, et al., 2014).[[1]](#footnote-1) In the past several decades microfinance has gained popularity among policymakers and other stakeholders and there have been concerted efforts to expand microfinance programs with the objective of promoting development and reducing poverty (Buera, et al., 2014). Theoretical direct links of microfinance activity to poverty reduction include increased entrepreneurship and increased consumption by households and individuals. Indirect links primarily relate to the development of financial markets in an economy (International Finance Corporation (IFC), nd).

A number of studies focused on the relationship between microfinance activities and poverty have now been produced, the great majority being micro-level evaluations relying on household or entrepreneurial data (Hulme & Mosley, 1996; Imai, Arun, & Annim, 2010; Kanz, 2012; Khandker, 2005; Mosley, 2001; Wydick, 1999; and others) or randomized control trials (Augsburg et al., 2015; Angelucci, et al., 2015; Banerjee, et al., 2009; Banerjee et al., 2015; Coleman, 1999; Cotler and Woodruff, 2008; Karlan and Zinman, 2010; Pitt and Khandker, 1998; and others). Other analytical approaches that have been employed include, but are not limited to: 1. case studies; 2. financial diaries/portfolios of the poor; and 3. other forms of quasi-experimental estimation techniques. These studies have produced mixed results regarding the impact of microfinance on poverty, in part because of differing methodologies and the use of different microfinance outcome measures (Imai, et al., 2010; 2012).

Fewer studies have considered the relationship on a macro/country-level. One simple explanation for this is that the size/reach of microfinance activity was once relatively small. In 1997, just 618 Microfinance Institutions (MFIs) served approximately 13.5 million clients worldwide (Microcredit Summit Campaign, 2012). By the end of calendar year 2013, more than 3,000 microfinance institutions served over 211 million borrowers with current loans, and affected 571.5 million of the “poorest” people, a number approaching the population size of Latin America (Buera, et al., 2014; Microcredit Summit Campaign, 2015).[[2]](#footnote-2) This means that between 1997 and 2013 the number of borrowers served by microfinance grew by almost 19 percent annually.[[3]](#footnote-3),[[4]](#footnote-4) In less than two decades, microfinance had grown from a small experiment to a global movement on a scale at which macroeconomic considerations arguably become relevant. The other primary reason for the relative dearth of macro-level analysis of microfinance is that for many years there was no source of reliable or comprehensive data characterizing microfinance activities for entire countries/regions.

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| Figure 1. Growth of Microfinance Coverage as Reported to the Microcredit Summit Campaign, 1997-2013 |
|  |
| Source: The Microcredit Summit Campaign, “State of the Microcredit Summit Campaign Report”, 2012-2015 reports. |

Despite the growth in size and in interest in academic and policy circles, the macroeconomic effects of microfinance are still unknown and quantitative analyses of microfinance programs are still mostly limited to micro-level evaluations (Buera, et al., 2014; Imai, et al., 2012). Of the existing literature regarding microfinance and poverty on a macro scale, Imai, Gaiha, Thapa, and Annim (2010; 2012) provide the most relevant econometric analysis of the impact of microfinance on poverty. Imai, et al. (2010; 2012) used cross-sectional and panel datasets constructed from the Microfinance Information Exchange (MIX) and the World Bank to test the hypothesis that microfinance reduces poverty at the macro level. Analyzing a cross-section covering 48 countries for 2007 and a panel covering 61 countries for 2003 and 2007, the authors found a statistically significant inverse relationship between Microfinance Institutions’ (MFIs’) gross loan portfolio per capita and poverty. Analysis by Miled and Rejeb (2015), which is in most respects a reproduction of Imai’s, produced similar results. Other recent works focused on the relationship between microfinance and the macroeconomy include Ahlin, Lin, and Maio (2011), Ahlin and Lin (2006), Alimukhamedova (2014), Donou-Adonsou and Sylwester (2016), Buera, Kaboski, and Shin (2014), Kai and Hamori (2009), and Perossa and Marinaro (2015), among others.

Continuing technological and institutional innovations suggest that the microfinance industry will continue to grow as new methods of delivery and service models emerge (IFC, nd), heightening the importance of understanding microfinance’s effects. Furthermore, micro-level studies may not apply to impacts on the entire country. For example, introducing microfinance may promote the development of the entire financial system, having indirect positive impacts on economic growth and poverty that go beyond the impact of microfinance on specific borrowers. For this reason, further examination of the impact of microfinance on a macro level can provide important insight for development agencies, governments, and other policymakers interested in the effects of microfinance as a policy tool.

*Research Goal*

I am studying microfinance because I want to determine if the expansion of loans to poor and low-income clients has any impact on a country’s poverty level. This will help to inform whether or not microfinance is a useful policy tool for combatting poverty. More specifically, the goal of this analysis is to both verify the findings of previous studies focused on the effects of microfinance on poverty at the macro level, as well as enrich the frameworks of Imai et al. (2010; 2012) and Miled and Rejeb (2015) by using more recent data, using a panel covering a longer time-period, and examining a number of factors not considered in the previous studies.

This project uses panel data covering approximately 70 developing countries for the years 1999-2014 to analyze the impact of microfinance activity (scale/volume—not performance/quality) on poverty. The dataset was assembled from data from the Microfinance Information Exchange (MIX) and the World Bank’s PovcalNet and World Development Indicators (WDI) databases. As noted by Imai et al. (2012), relatively few analyses have used MIX data for measures of microfinance activity on a macro level (p. 1676). This study also uses the most recent World Bank poverty estimates, released in October 2016 (World Bank, PovcalNet).

The rest of this paper is organized as follows. The subsequent section reviews relevant theory and literature. Section 3 provides a description of the data used in the analysis, any associated limitations, and the individual variables that are examined. Section 4 outlines model specifications and hypotheses. Results of the analysis are reported and discussed in Section 5 and concluding observations are offered in the final section.

# 2. Background & Literature Review

According to the World Bank, just under 62 percent of adults worldwide had an account either at a financial institution or through a mobile money provider in 2014. In low-income countries, the share of adults with an account ranges from 22.3 percent to 27.5 percent, compared with more than 90 percent in high-income countries (see Table 1 below for further details) (World Bank, Global Findex database). One reason for the relatively low figures in low-income countries is that banks face obstacles to serving the poor. There may be a number of such obstacles, but the most important are likely banks’ incomplete information about poor borrowers (and the high costs of obtaining information) and poor borrowers’ lack of collateral to offer as security to lenders. These problems of adverse selection and moral hazard can be made worse by the challenge of enforcing contracts in regions with weak judicial systems. Even if these problems were eliminated, banks still typically face relatively high transactions costs when working in poor communities because managing many small transactions is more expensive than servicing fewer large transactions with richer borrowers. The starting point for microfinance is that alternative ways of delivering loans to certain borrowers are needed, in part because of the issues mentioned above (Beatriz and Morduch, 2010, p. 7-8).

Table 1. Share of Adults with an Account by Region, 2014

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| --- | --- | --- | --- |
| **Region** | **% With Account (Ages 15+)** | **% With Account at a Financial Institution** | |
| **Ages 15+** | **Ages 25+** |
| Low-income countries | 27.5% | 22.3% | 26.0% |
| Middle-income countries | 57.6% | 57.1% | 60.9% |
| High-income countries | 90.6% | 90.6% | 92.5% |
| *World* | *61.5%* | *60.7%* | *65.1%* |
| Sources: 1. The World Bank, Global Findex database. <http://datatopics.worldbank.org/financialinclusion/>. 2. The World Bank (2015). “Findex Note 14/1: Measuring Ownership and Use of Accounts”. Notes: The share of adults with an account is the percentage of respondents who report having an account by themselves or together with someone else—at either a financial institution or through a mobile money provider. The first category includes accounts at banks and other financial institutions, such as credit unions, cooperatives, and microfinance institutions. The second consists of phone-based mobile money accounts used to pay bills, send or receive remittances, or collect payments. | | | |

Microfinance Institutions (MFIs) are distinct from large, perhaps government-sponsored programs (for example, national savings schemes or post office savings banks) and from purely commercial, small-scale, possibly informal financial institutions dealing with the poor (for example, village moneylenders, pawnshops, and informal transfer systems). What distinguishes MFIs is their orientation to fill gaps left by these commercial or government institutions in the provision of financial services to poorer households and small-enterprises. The term “microfinance institutions” generally refers to financial institutions that are characterized by their commitment to serving usually poor households and small enterprises. That commitment may replace or supplement other public or private objectives such as the mobilization of savings to finance government operations, maximization of shareholder value, or the direction of investment into priority sectors. In common usage, MFIs are understood as distinct from the other types of lending/financial services mentioned above (Hardy, et al. 2002. p. 3-4).[[5]](#footnote-5)

Among MFIs there is great heterogeneity—in the nature of their operations, size, and financial performance (Hardy, et al. 2002. p. 4). Furthermore, the range of institutions offering microfinance services has been expanding. NGOs (Non-governmental Organizations), credit unions, cooperatives, and sectors of government banks are other examples of institutions that offer microfinance. There has also been an emergence of “for-profit” MFIs, sometimes called “Non-banking Financial Companies” (NBFCs) or “Non-bank Financial Institutions” (NBFIs), which provide services similar to those of banks but are usually subject to different regulations (Buera, et al. 2014, p. 8; “Micro Financial Institutions”. nd.; MIX, 2016. p. 30). MIX classifies MFIs by the charter type under which the MFI is registered. MIX classifies organizations as banks, credit unions/cooperatives, NGOs, or non-bank financial institutions (NBFIs) (MIX, 2016. p. 30).

Table 2 below shows the legal status of MFIs reporting to MIX in 2014. According to these data, Non-bank Financial Institutions (NBFIs) and Nongovernmental Organizations (NGOs) play a large role in global microfinance. Among the organizations reporting to MIX in 2014, NBFIs constitute 37 percent of institutions, hold almost 30 percent of the total loan value, and reach 43 percent of borrowers. NGOs account for just over 30 percent of the institutions, 10 percent of loans, and 27 percent of borrowers. Banks make up only 10.6 percent of institutions, but, because they are larger, account for almost 27 percent of borrowers and 51 percent of loan value (MIX, 2016; Buera, et al., 2014. p. 8).

Table 2. MFIs Reporting to the Microfinance Information Exchange in 2014 by Legal Status: Select Operational Indicators

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| --- | --- | --- | --- |
|  | **Count** | **# of Active Borrowers (Millions)** | **GLP (USD)**  **($ Millions)** |
| NBFI | 394 | 48.43 | $26,053.4 |
| NGO | 325 | 30.98 | $8,971.2 |
| Bank | 113 | 30.01 | $44,575.9 |
| Credit Union/Coop | 192 | 1.87 | $7,121.6 |
| Rural Bank | 15 | 1.03 | $488.4 |
| *Total* | *1,064* | *112.59* | *$87,349.8* |
| Source: MIX. (2016). “Global Outreach & Financial Performance Benchmark Report – 2014”. Appendix, p. 29.  Notes: 1. Numbers do not sum to total. 2. MIX’s definition for each organization type is as follows: *Non-Bank Financial Institution (NBFI):* An institution that provides similar services to those of a Bank, but is licensed under a separate category. The separate license may be due to lower capital requirements, to limitations on financial service offerings, or to supervision under a different state agency. In some countries this corresponds to a special category created for microfinance institutions. *Non-governmental organization (NGO):* An organization registered as a non-profit for tax purposes or some other legal charter. Its financial services are usually more restricted, usually not including deposit taking. These institutions are typically not regulated by a banking supervisory agency. *Bank:* A licensed financial intermediary regulated by a state banking supervisory agency. It may provide any of a number of financial services, including: deposit taking, lending, payment services, and money transfers.  *Credit Union/Cooperative:* A non-profit, member-based financial intermediary. It may offer a range of financial services, including lending and deposit taking, for the benefit of its members. While not regulated by a state banking supervisory agency, it may come under the supervision of regional or national cooperative council. *Rural Bank:* Banking institution that targets clients who live and work in non-urban areas and who are generally involved in agricultural-related activities. | | | |

## 2.1. Microfinance & Poverty: Theoretical Links

When considering the effects of financial development an important distinction is between the effects on the household/firm-level and the aggregate effects. On the one hand, an extensive set of empirical literature has explored the impact of greater access to financial services on household welfare or firm growth. Alternatively, the aggregate finance and development literature has concentrated on the role of financial sector development in allocating resources to their most productive uses, improving governance across the economy, and fostering innovation and competition (Beck, 2016, p.11-12). Similarly, potential poverty reducing effects of microfinance should be considered at both the individual level, as well as at the aggregate level. This distinction is not only academically significant, but also has important policy implications (Beck, 2016, p.12). The diagram below outlines some of the possible direct and indirect links between microfinance and poverty.

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| Figure 2. Microfinance: Direct and Indirect Transmission Links to Poverty |
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| Source: International Finance Corporation (IFC) (nd). “Poverty Literature Review: Microfinance and Poverty Reduction.” Note: figure is a modified version of the figure presented in the IFC literature review sourced. |

*Direct*. At the individual or micro-level, microfinance theoretically impacts poverty by easing credit constraints faced by poor individuals and businesses. The most basic underlying theory regarding the direct link between microfinance and poverty is related to access to capital and output. This theory assumes that a microfinance client is the operator of an income generating activity for which output is constrained either by a lack of capital or by high marginal costs of credit relative to marginal returns. By providing access to cheaper capital microfinance may ease that constraint, facilitating increases in output, profits, net income and ultimately, the welfare of the client (de Mel et al., 2008; Duvendack et al., 2011 as cited in Awaworyi, 2014, p. 2). The other theoretical direct effect of microfinance on poverty is related to the use of microfinance loans by households and individuals not for entrepreneurial purposes, but to meet consumption needs. Microcredit for consumption purposes may reduce poverty by allowing poor individuals/families to invest in human capital, such as borrowing to invest more in their education or that of their children, which improves their access to higher paying jobs (Johnston and Morduch, 2008; Banerjee et al., 2010; Crépon et al., 2011; Buera, Kaboski and Shin, 2011 as cited in Beck, nd). Credit for consumption purposes may also help reduce poverty by simply allowing individuals/households to better cope with external shocks and achieve consumption smoothing (Kai and Hamori, 2009).

Another important aspect of the microfinance movement is gender. Microfinance programs often target women as clients and women make up a large share of total microfinance borrowers. Women represented 81 percent of total borrowers among MFIs reporting to MIX in 2014 (MIX, 2016. p. 2). From a lenders perspective, there are at least three potential advantages to serving women. The first is purely financial: women often prove to be more financially responsible and have better repayment performance than men (Armendariz de Aghion and Morduch, 2010. p. 183; Morduch, et al., 2003. p. 7). The other two advantages relate to the pursuit of social objectives—specifically, aiming resources to women may deliver stronger development impacts. One reason for this is that women may tend to be more concerned about health and education than men, and thus more likely to use loans to help their children/family by investing in those areas. The other reason is that women are overrepresented among the poorest of the poor, and are often oppressed by social norms and systemic gender inequities. Thus, microfinance has been proposed by advocates as a road to “gender empowerment” (Armendariz de Aghion and Morduch, 2010. p. 183-184). Advocates argue that microfinance can empower women to be more confident and assertive, increase their bargaining power in the household and community, and help them promote their rights vis-à-vis their husbands or other male family members (Armendariz de Aghion and Morduch, 2010. p. 191-192; Morduch, et al., 2003. p. 7).

*Indirect*. Theoretical indirect links between microfinance and poverty reduction primarily relate to the development of financial markets in an economy (IFC, nd). There are many ways in which the financial sector can “develop”. Of the forms of development outlined by the Department for International Development (DFID) (2004), one can reasonably associate microfinance/the presence of microfinance institutions with at least one of the following financial sector developments: improving the efficiency and competitiveness of the sector; increasing the range of financial services that are available; increasing the diversity of institutions which operate in the financial sector; increasing the amount of money that is intermediated through the financial sector; and expanding access to financial services to more of the population. By contributing to financial development, microfinance may contribute to poverty reduction on a macro level. However, as noted by Thorsten Beck (nd), the way in which financial deepening impacts poverty is not certain: “By now, there is solid evidence that financial deepening can contribute to poverty alleviation. The debate is still on the channels.” Some of the channels through which microfinance might impact poverty are: 1. a general pro-growth effect; 2. an improved allocation of resources; and 3. occupational shifts/pulling more people into the formal labor market (DFID, 2004; Beck, 2015; IFC, nd; Loury, 1981; Giné and Townsend, 2004; Khandker, 1998; Morduch, et al., 2003). Lastly, investments in microfinance may also induce “demonstration effects” in terms of increased competition, institutional development, or macroeconomic policies that can lead to broader financial deepening and poverty reduction (IFC, nd).

*Potential Negative Impacts.* As a final note, it should be acknowledged that in addition to the possible benefits of microfinance, there may also be some associated negative impacts, particularly when it comes to the use of microfinance loans (versus other services like savings or insurance). Like traditional loans, the impact of credit depends on a variety of factors, including its specific use (Crowther, 2015. p. 84). Some have raised concerns that microcredit used for non-productive/non-business uses may not promote growth, and may even be harmful if debt grows to unsustainable levels. In response to evidence that microcredit has often been used to cover basic consumption needs, the microfinance sector has used consumption smoothing as another argument in support of microfinance. However some argue that this can actually lead poor individuals to substitute microcredit for non-existent income in an unsustainable way. For example, increasing dependency on microcredit, along with high interest rates, can result in a growing share of the unstable income of the poor being siphoned off to cover interest charges. Srinivasan (2010) suggests that this is the dynamic responsible for a microfinance crisis in Andhra Pradesh, India (Bateman, 2011. p. 2; Srinivasan, 2010 as cited in Bateman, 2011). Bateman (2011) argues that: “by conferring social legitimacy upon microfinance, rather than loan sharks, the stage was set for the poor to become open to the idea of going into debt.” (Bateman, 2011. p. 2). Even if microfinance clients are able to make the necessary loan payments, consumption loans are hypothetically less likely to contribute to sustainable increases in income compared to fixed or working capital loans (Crowther, 2015. p. 84). With respect to these issues the evidence about the impact of microfinance remains controversial—some studies suggesting that microfinance is effective and benefiting clients and other literature suggesting otherwise (Awaworyi, 2014. p. 2).

## 2.2. Literature Review

A number of studies focused on the relationship between microfinance activities and poverty have now been produced, the great majority being micro-level evaluations relying on household or entrepreneurial data (Hulme & Mosley, 1996; Imai, Arun, & Annim, 2010; Kanz, 2012; Khandker, 2005; Mosley, 2001; Wydick, 1999; and others) or randomized control trials (Augsburg et al., 2015; Angelucci, et al., 2015; Banerjee, et al., 2009; Banerjee et al., 2015; Coleman, 1999; Cotler and Woodruff, 2008; Karlan and Zinman, 2010; Pitt and Khandker, 1998; and others). Other analytical approaches that have been employed include, but are not limited to: 1. case studies; 2. financial diaries/portfolios of the poor; and 3. other forms of quasi-experimental estimation techniques. These studies have produced mixed results regarding the impact of microfinance on poverty, in part because of differing methodologies and the use of different microfinance outcome measures (Imai, et al., 2010; 2012).

Micro-level analysis has a number of drawbacks, one significant one being the difficulty in separating the causal effects of microfinance loans from selection effects (Imai, et al., 2012; Beatriz and Morduch, 2010). Furthermore, micro-level studies may not apply to impacts on the entire country. For example, as discussed above, introducing microfinance may promote the development of the entire financial system, having indirect positive impacts on economic growth and poverty that go beyond the impact of microfinance on specific borrowers. For this reason, examination of the impact of microfinance on a macro level can provide important insight for development agencies, governments, and other policymakers interested in the effects of microfinance as a policy tool.

### Macro-Level Analyses: Findings from Relevant Studies

Imai, Gaiha, Thapa, and Annim (2012) provide the most relevant country-level analysis of the impact of microfinance on poverty.[[6]](#footnote-6) The authors used cross-sectional and panel datasets constructed from the Microfinance Information Exchange (MIX) and the World Bank to test the hypothesis that microfinance reduces poverty at the macro level. Their analysis found an inverse relationship between Microfinance Institutions’ (MFIs’) gross loan portfolio (GLP) per capita and poverty. Analyzing a cross-section covering 48 countries in developing regions for 2007 Imai, et al. apply both ordinary least squares (OLS) and Instrumental Variables (IV) estimation to test the effect of GLP per capita of MFIs on poverty (poverty measures at $1.25/day 2005 $PPP).[[7]](#footnote-7) Other variables included in their cross-sectional estimations include gross domestic product (GDP) per capita, domestic credit as a share of GDP, and regional dummies. In addition to cross-sectional estimations, the authors estimate the effect of FMIs’ GLP per capita on poverty using a panel covering 61 countries for 2003 and 2007. Due to data constraints, the authors construct poverty data for their panel by taking averages of poverty for the period 2000-03 and 2004-07. Including the same set of explanatory variables Imai, et al. (2012) apply pooled OLS, fixed effects (FE), and random effects (RE) to test the hypothesis that higher MFI GLP per capita results in poverty reduction at the macro level.

All of the cross-sectional estimations in Imai, et al. (2012) show GLP per capita being negatively associated with the poverty headcount ratio, poverty gap, and squared poverty gap and almost all coefficients are significant at the 1% or 5% level. For the poverty headcount ratio, Imai, et al.’s cross-sectional regressions yield statistically significant coefficient estimates of between -1.40 and -3.80 for log of GLP per capita of MFIs. According to these results, a 10 percent increase in MFIs’ loan portfolio per capita reduces poverty by between 0.140 and 0.380 percentage points. The authors’ FE and RE estimations show a similar pattern, however, with one exception, the negative relationship between GLP per capita and poverty is only significant when using random effects (regional effect) and pooled OLS models. For the poverty headcount ratio, the RE estimations show statistically significant coefficient estimates of between -0.91 and -1.59, suggesting that a 10 percent increase in MFI loan portfolio per capita reduces poverty by between 0.091 and 0.159 percentage points (p.1679).

Analysis by Miled and Rejeb (2015), which is in most respects a reproduction of that of Imai, Gaiha, Thapa, and Annim (2012), produced similar results. Miled and Rejeb use cross-sectional data covering 40 developing countries for 2011 and a two-period (2005 and 2011) panel data covering 57 developing countries. Their dataset is also constructed from the Microfinance Information Exchange (MIX) and the World Bank. Miled and Rejeb constructed poverty data for their panel by taking averages of poverty for 2000–05 and 2006–011 (poverty measures at $1.25/day 2005 $PPP). Like Imai, et al. (2012), Miled and Rejeb apply OLS and IV estimation to their cross-sectional data and pooled OLS, FE, and RE estimation to their panel data.[[8]](#footnote-8) One unique element of Miled and Rejeb’s study is their selection of microfinance institutions to include in their sample. In their collection of MIX data, the authors wanted to focus only on microfinance institutions with high levels of informational transparency. Therefore, they included only “those 3-5 diamonds levels which is the highest level of disclosure to its outreach, impact and financial data, audited financial statements and rating/evaluations” (p.706). Other distinctive aspects of the authors’ analysis are the inclusion of additional control variables (inflation and “openness”) and estimation of the effect of MFIs’ GLP per capita on consumption expenditure per capita as a proxy for poverty. Miled and Rejeb’s results are similar to Imai et al.’s. For the poverty headcount ratio, Miled and Rejeb’s regressions using cross-sectional data yield statistically significant coefficient estimates of between -1.50 and -3.14 for log of GLP per capita of MFIs. The authors’ panel data results show somewhat larger effects than Imai et al., with pooled OLS and RE models showing estimates of -2.21 and -3.13, respectively (statistically significant at the 1% level). Their fixed effects model produces a coefficient estimate of -1.40 (10% level) (p. 709-711). One interpretation of these results would be that a 10 percent increase in MFI GLP per capita results in a reduction in poverty of between 0.14 and 0.313 percentage points, depending on the model.

Despite the findings of Imai et al. (2012) and Miled and Rejeb (2015) that countries with higher MFI gross loan portfolio have lower poverty, the relationship is far from certain. Donou-Adonsou and Sylwester (2016) examine the relationship between poverty and financial development as measured by the size of either traditional banks or microfinance institutions (p. 89). They compare the extent to which each contributes to poverty reduction using bank credit (measured as bank credit as a % of GDP) and MFI credit (measured as GLP of as a % of GDP) as the main financial development indicator and find that banks reduce the poverty headcount ratio and poverty gap, but have no significant effect on the squared poverty gap (poverty measures at $1.25/day 2005 $PPP). On the other hand, their results indicate that MFIs have no impact on poverty, regardless of the measure used (p. 82, 89). Donou-Adonsou and Sylwester come to these results by applying FE and IV models to a panel covering 71 developing countries from 2002-2011.[[9]](#footnote-9) To construct their dataset, the authors combine data from a number of sources. Like other authors, they use MIX and World Bank data. Their data regarding traditional banks comes from Beck et al. (2013).

Donou-Adonsou and Sylwester test the effect of bank/MFI credit on poverty individually and with both variables included in the same model. They also control for GDP per capita and the Gini index (p. 84-86). Their results show a negative relationship between bank credit as a percent of GDP and the poverty headcount ratio and poverty gap, regardless of whether or not MFI credit is included. For the poverty headcount ratio, the coefficients of log of bank credit are statistically significant at the 1-5% level and range from -0.529 (fixed effects without instruments; both bank credit and MFI credit included in the model) to -0.685 (with instruments; both bank credit and MFI credit). The authors’ dependent variable is also expressed in log, therefore these results suggest that a 10 percent increase in bank credit reduces the fraction of the population in poverty by between 5.3%-6.9%. Donou-Adonsou and Sylwester’s findings support those of other authors (Honohan, 2004; Jalilian and Kirkpatrick, 2005; Beck et al., 2007; Jeanneney and Kpodar, 2011; Sehrawat and Giri, 2015) who find that financial development lowers poverty, but suggest that any effect of MFI credit on poverty reduction is at most small (Donou-Adonsou and Sylwester, 2016, p. 87).

Donou-Adonsou and Sylwester offer several possible explanations for why banks might show poverty reducing effects while MFIs do not, particularly given the specific focus of MFIs on helping the poor. They suggest that bank credit used for investments in infrastructure may have various spillovers leading to lower poverty, such as the hiring of poor workers, reduced transportation costs, or access to roads facilitating market access. Medium to large companies making such investments would not go to microfinance institutions to seek funding given the size of MFI portfolios, the authors suggest (p. 87-88). Donou-Adonsou and Sylwester also hypothesize that traditional banks could be more successful in reducing poverty because some banks facing competition from MFIs have actually begun lending to the poor also. Some banks do indeed offer microcredit services and small businesses may find bank loans cheaper as some evidence suggests that MFIs charge higher interest rates than traditional banks, on average (Donou-Adonsou and Sylwester, 2016, p. 88). In terms of lending, some have suggested that due to inadequate management and deficiencies in control of their activities, the quality of MFIs’ loan portfolios is sometimes poor, making it difficult to reach efficiency levels to cover their costs (Holden and Prokopenko, 2001 as cited in Donou-Adonsou and Sylwester, 2016, p. 88). On the demand side, Donou-Adonsou and Sylwester cite Chowdhury (2009) who points out that borrowers may lack the business skills and marketing information to obtain loans to expand business activities and create jobs. Therefore, those that do possess such skills might be more successful at obtaining financing from traditional banks (Donou-Adonsou and Sylwester, 2016, p. 88).

Finally, Donou-Adonsou and Sylwester’s suggest the greater size of banks may explain their comparative ability to reduce poverty, noting that bank credit and assets are many times larger than that of MFIs which provides much greater potential for their changes in lending to impact the poor. Further, microfinance loans are almost always small, so it’s possible that any effects could be contained locally and therefore not impact poverty at the country level (Donou-Adonsou and Sylwester, 2016, p.88). It is interesting that Donou-Adonsou and Sylwester find that banking development can help combat extreme poverty, but may fail to reach the poorest (in that they find no significant effects of bank credit on the squared poverty gap) (p. 89). It is possible that microfinance development has the potential to alleviate poverty by reaching some of the poorest clients, but is still at an infant stage where it has not reached enough clients to have effects on the aggregate level.

## 2.3. Contribution to Previous Work

Given mixed results and the still limited number of studies of the effect of microfinance on poverty at a macro level, Donou-Adonsou and Sylwester (2016), among others, have called for further study of the issue. This analysis adds to the evidence base regarding the use of microfinance as a policy tool for combatting poverty on a macro level. The goal of the analysis is to both verify the findings of previous work, as well as enrich the frameworks of previous studies by Imai et al. (2012) and Miled and Rejeb (2015). This study builds on those analyses by using more recent data and using a panel covering a longer time-period. This analysis uses panel data covering approximately 70 developing countries for the years 1999-2014 (unbalanced panel). A longer panel dataset is important because while MIX data date back to 1994, most MFIs were reluctant to submit their records for public use before 2002 (Imai, et al., 2012, p. 1684) and MFI reporting standards and participation have continued to improve. The longer span of 1999-2014 will also likely provide a more thorough/accurate picture of microfinance loan volume than the previous studies’ two period panels. Another strength of this analysis is that it uses the most recent World Bank poverty estimates, released in October 2016 (World Bank, PovcalNet). When previous studies by Imai et al. (2010; 2012) and Miled and Rejeb (2015) were published, the World Bank’s poverty estimates covered a smaller range of countries and years. Due to this constraint, Imai et al. (2010; 2012) constructed poverty data for their panel by taking averages of World Bank poverty estimates for 2000-2003 and 2004-2007. Similarly, Miled and Rejeb (2015) applied averages for 2000-2005 and 2006-2011. The World Bank data released in 2016 provide estimates for more years for each country, which means that this analysis does not need to construct poverty estimates by taking averages across years to have sufficient observations. Finally, a number of factors not considered in the frameworks of Imai et al. (2012) and Miled and Rejeb (2015) are explored in this study, such as country income-level and additional indicators of microfinance activity.

# 3. Data

The dataset used in this project was assembled from the Microfinance Information Exchange (MIX) and the World Bank’s PovcalNet and World Development Indicators (WDI) databases.

## 3.1. MIX Data

The Microfinance Information Exchange (MIX) was established in 2002 and provides data on financial inclusion outreach and financial performance indicators at the industry, country, and regional level (Imai, et al., 2012; MIX, “Who We Are”). MIX collects data from Microfinance Institutions (MFIs) and other types of financial services providers (FSPs) based on: set formats and reporting standards, validation of information with a two-step internal and external cross-checking system, and standardization of the raw data to allow for comparison (Imai, et al., 2012; MIX, “About Our Data”). MIX then calculates and reports a series of ratios and indicators based on the raw data collected (MIX, “FAQs”). The MIX Market platform allows users to access historical data characterizing the presence and activity of MFIs at the country or region level, such as gross loan portfolio (GLP), the number of MFIs, and the number of borrowers, among other indicators.

For this analysis, gross loan portfolio (GLP) is used as the primary measure of microfinance activities in a country, as it represents actual funds disbursed to households (Imai, et al., 2012, p. 1676).

* *Microfinance Institutions’ (MFIs’) Gross Loan Portfolio (GLP) Per Capita*: GLP divided by total population. GLP is defined by MIX as, “all outstanding principals due for all outstanding client loans. This includes current, delinquent, and renegotiated loans, but not loans that have been written off. It does not include interest receivable.” (MIX, “Glossary”).[[10]](#footnote-10)

### MIX Data: Cautions/Limitations

MIX data should be approached with caution for a number of reasons. As outlined by Imai et al. (2010; 2012) and other authors (Ahlin et al., 2011 as cited in Imai, 2012), potential problems arise because:

* MIX may not be able to distribute questionnaires to all MFIs in every country, particularly if MFIs are small or recently established;
* MIX data may suffer from sample selection bias because not all MFIs surveyed by MIX respond;
* Even though MIX imposes careful cross-checking systems and ranks the reliability of data, there may be measurement errors arising from the fact that MFIs self-report (p. 1684).

Previous analyses have attempted to check how significant these problems might be. For example, to cross-check potential bias arising from self-selection in the MIX data, Imai et al. (2012) estimate variants of their econometric models with different sub-samples of MIX data chosen based on specific criteria, such as the level of validity of the data submitted by MFIs. The authors find their results to be broadly similar and consistent regardless of which sub-samples are included.[[11]](#footnote-11) They also compare the GLP per capita (based on MIX data) with several measures of microfinance activity at country levels from World Bank WDI (2011) and find positive and significant pairwise correlations for all the variables.[[12]](#footnote-12) The results of the checks performed by these authors suggest that MIX data aggregated at country levels can be accepted with some confidence as an accurate representation of microfinance activity. Furthermore, the MIX data cover a large share of microfinance clients worldwide and MIX ultimately provides the largest and most comprehensive dataset on microfinance activities (Cull and Morduch, 2007, 2011 as cited in Imai, et al., 2012).

## 3.2. World Bank International Poverty Data

The World Bank’s PovcalNet database provides data on a number of poverty measures that allow comparison across countries. Beginning in 1990 the World Bank has worked to implement a common standard for measuring extreme poverty by adjusting for differences in the purchasing power of currencies to establish an international poverty line. The World Bank’s international poverty line is linked to what poverty means in the poorest countries, therefore it is based on the poverty line typical of the poorest countries in the world. World Bank poverty data are based on primary household survey data collected from World Bank country departments and government statistical agencies (The World Bank, WDI, metadata for select indicators).

Currently the World Bank’s extreme poverty line is set at $1.90 in 2011 purchasing power parity (PPP) terms. This value represents the average of the poverty lines found in the poorest 15 countries ranked by per capita consumption (The World Bank, WDI, metadata for select indicators). In October of 2016 the World Bank published estimates of global poverty from 1981 to 2014 based on household surveys across 138 developing countries and 21 high income countries. The World Bank applies PPP exchange rates for household consumption from the 2011 International Comparison Program to these surveys to generate poverty estimates. The more than two million households randomly sampled for the 2016 poverty estimate represent 87 percent of the population of the developing world (World Bank, PovcalNet).

The two World Bank international poverty measures used in this analysis are:

* *Poverty headcount ratio at $1.90 [or $3.10] a day*: The poverty headcount ratio represents the percentage of the population living on less than $1.90 [or $3.10] a day at 2011 international prices. This measure reflects the incidence of poverty (The World Bank, WDI, metadata for select indicators).
* *Poverty gap at $1.90 [or $3.10] a day*: The poverty gap is the mean shortfall in income or consumption for the population from the $1.90 [or $3.10] a day mark (counting the nonpoor as having zero shortfall), expressed as a percentage of the poverty line. This measure reflects the depth of poverty as well as its incidence (The World Bank, WDI, metadata for select indicators).

### World Bank Poverty Estimates: Cautions/Limitations

* Timeliness, frequency, quality, and comparability of household surveys: The World Bank notes that despite progress over the last decade, the timeliness, frequency, quality, and comparability of household surveys need to improve, particularly in the poorest countries. The quality and availability of poverty monitoring data remains low in small states, low-income countries, countries with fragile situations, and even some middle-income countries. This creates uncertainty regarding the magnitude of poverty reduction over time (The World Bank, WDI, metadata for select indicators).
* Data quality issues in measuring household living standards: The surveys used to estimate poverty ask detailed questions about sources of income and how it was spent. When considering living standards, consumption may be a more relevant measure than income (for example, income can vary over time, even if living standards do not). The World Bank notes that income is also generally more difficult to measure accurately. However consumption data is not always available, and therefore the estimates reported by the World Bank use consumption data for only about two-thirds of countries. Even similar surveys of consumption may not be strictly comparable due to timing differences or differences in the training of the people recording survey responses (The World Bank, WDI, metadata for select indicators).
* Comparing countries at different levels of development: Differences in the relative importance of the consumption of nonmarket goods pose a potential problem for comparing countries at different levels of development. The local market value of all consumption, including own production (particularly important in less developed, rural economies) would ideally be included in total consumption expenditure estimates, but may not always be. Although valuation methods vary, most survey data used by the World Bank now include valuation of consumption or income from own production (The World Bank, WDI, metadata for select indicators).

## 3.3. Summary of Variables

Control variables that are included in the poverty equation include gross domestic product (GDP) per capita and domestic credit as a share of GDP, among others. All other variables are sourced from the World Bank’s World Development Indicators database. The table below provides a summary.

Table 3. Description of Variables

| **Variable** | **Description** |
| --- | --- |
| **Poverty** |  |
| Poverty headcount ratio | The percentage of the population living on less than $1.90 [or $3.10] a day (2011 PPP); The percentage of population living in households with consumption or income per person below the poverty line. |
| Poverty gap | Mean shortfall in income or consumption from the $1.90 [or $3.10] a day mark (2011 PPP), mark (counting the nonpoor as having zero shortfall), expressed as a percentage of the poverty line.  The poverty gap (PG) can be written as:    Where N is the total population, q is the number of people who are poor, z is the poverty line, and yi is the income of each individual (the sum is only taken for those who are poor, q) |
| Microfinance |  |
| MFI’s gross loan portfolio per capita | Microfinance Institutions’ (MFIs’) Gross Loan Portfolio (GLP) divided by total population  (calculated by author). GLP is in US$. |
| **Other Control Variables** | |
| GDP per capita | Gross domestic product (GDP) per capita (PPP constant 2011 international $). |
| Domestic credit to  private sector by banks  (% of GDP) | Refers to the financial resources provided to the private sector by depository corporations (deposit taking corporations except central banks), such as through loans, purchases of nonequity securities, and trade credits and other accounts receivable, that establish a claim for repayment. For some countries these claims include credit to public enterprises. |
| Population density | People per sq. km of land area. |
| Population growth (%) | Annual growth rate of midyear population (%). |
| Rural population growth (%) | Annual growth rate of rural population (%). Rural population refers to people living in rural areas as defined by national statistical offices and is calculated as the difference between total population and urban population. |
| Age dependency ratio (%) | Ratio of dependents to the working age population (%). Dependents are defined as people younger than 15 or older than 64 years of age and the working age population is defined as people ages 15-64. |
| Fertility rate, total | Births per woman. |
| Labor force participation rate (%) | Percentage of the population ages 15+ who supply labor for the production of goods/services |
| Employment to population ratio (%) | Proportion of a country's population that is employed. Ages 15 and older are generally considered the working-age population. |
| Agricultural land  (% of land area) | Agricultural land as a proportion of total land area. |
| Agriculture value added per worker | Agriculture value added per worker is a measure of agricultural productivity. Value added in agriculture measures the output of the agricultural sector (ISIC divisions 1-5) less the value of intermediate inputs. Agriculture comprises value added from forestry, hunting, and fishing as well as cultivation of crops and livestock production. Data are in constant 2010 US$. |
| Government expenditure on education (% of GDP) | General government expenditure on education (current, capital, and transfers) expressed as a percentage of GDP. Includes expenditure funded by transfers from international sources to government. General government usually refers to local, regional and central governments. |
| Note: See “Variable Definition & Notes” at the end of this paper for long definitions. Sources: 1. Microfinance Information Exchange, Inc. *Glossary*. 2. World Bank, World Development Indicators database. 3. The World Bank. PovcalNet. *PovcalNet: an online analysis tool for global poverty monitoring.* 4. Klugman, Jeni, ed. 2002. *A Sourcebook for Poverty Reduction Strategies: Volume 1: Core Techniques and Cross-Cutting Issues.*  “Technical Note A.1 Measuring Poverty and Analyzing Changes in Poverty Over Time”. Washington, DC: World Bank. | |

# 4. Methodology & Hypotheses

## 4.1. Methodology

To examine the relationship between Microfinance Institutions’ (MFIs’) gross loan portfolio (GLP) per capita and poverty this study uses panel data covering approximately 70 developing countries for the years 1999-2014. Using panel data takes account of changes in variables over time and unobservable country or regional-level effects (Imai, et al., 2012). A series of regressions are estimated for two dependent variables: the poverty headcount ratio and the poverty gap. The rationale for going beyond examining the simple poverty headcount ratio is that some have pointed out that microfinance/microcredit does not necessarily reach the poorest of the poor (Morduch, 1999 as cited in Imai, et al., 2012, p. 1677). Therefore, like previous studies have done, this analysis also estimates the effect of MFIs’ gross loan portfolio per capita on the poverty gap (a measure of depth of poverty) (Imai, et al., 2012, p. 1677). Both fixed effects (FE) and random effects (RE) models are estimated and Hausman tests are used to help determine the appropriate specification.

To examine the findings of Imai et al. (2012) and Miled and Rejeb (2015), I begin by including some of the same control variables—GLP per capita, GDP per capita, and domestic credit of banks as a share of GDP. I estimate FE/RE for the poverty headcount ratio at $1.90/day and $3.10/day (4 regressions) and FE/RE for the poverty gap at $1.90/day and $3.10/day (4 regressions), for a total of 8 regressions. From this limited specification, I then perform sensitivity analysis to see how the effect of GLP per capita on poverty changes as different explanatory variables are included.

The following equations describe fixed effects and random effects models estimating the relationship between gross loan portfolio per capita and poverty:

Fixed effects model: Povit = (α + ui) + β1GLPit + β2GDPit + β3CREDit + … γx…+ vit

Random effects model: Povit = α + β1GLPit + β2GDPit + β3CREDit + … γx…+ (ui + vit)

Where “Pov” is one of the two poverty measures (poverty headcount ratio or poverty gap). “GLP” indicates gross loan portfolio per capita. “GDP” indicates gross domestic product (GDP) per capita. “CRED” indicates the domestic credit of banks to the private sector as a share of GDP. γx is a vector of the other explanatory variables that may be included in the model (see Table 3). i=entity and t=time. ui is the fixed (or random) effect specific to each individual country. The error term is denoted by vit.

### Limitations

One limitation that may impact FE estimation that should be noted is that there may be some endogeneity between GDP and microfinance—according to Ahlin et al. (2011); Alimukhamedova (2014) macroeconomic growth is a strong predictor of microfinance performance. When macroeconomic growth is higher MFIs are found to cover costs better, due largely to lower default rates and operating costs. For RE estimation, an important limitation of this study is that it does not adequately address the likely endogeneity associated with MFIs’ gross loan portfolio (GLP). The endogeneity is associated with the bi-causal relationship between GLP per capita and poverty levels in a country. For example, governments and poverty-oriented development partners may provide more funds to MFIs located in poorer countries (Imai, et al., 2012, p. 1677). Previous studies have used Instrumental Variable (IV) estimation to account for endogeneity, first estimating GLP per capita by an instrumental variable and other controls, and then estimating poverty using the predicted GLP and other controls. Imai et al. use the cost of enforcing contracts at the country level and a 5-year lag of average of gross loan portfolio weighted by the number of MFIs for each country as instruments (p. 1677). Miled and Rejeb’s instruments are the cost of enforcing contracts at the country level and a 6-year lag of average of gross loan portfolio weighted by the number of MFIs for each country (p. 707). Donou-Adonsou and Sylwester use measures of ethnic tensions and rule of law at the country level for their IV estimation (p. 86). Given data and time constraints, this study does not include a similar estimation.

### Hypotheses

The main hypothesis is that higher MFIs’ gross loan portfolio per capita is associated with lower poverty at the country-level.

H0: B1=0

Ha: B1<0

With respect to the other variables included in the limited specification, GDP per capita is expected to be strongly inversely related with poverty, a relationship that has been widely confirmed in existing literature. The role of domestic credit as a share of GDP (a measure of financial development), is more complex, partly because financial development is both a cause and result of growth (Imai, et al., 2012, p.1676). Furthermore, because bank credit as a % of GDP is a measure of financial development and one of the potential impacts of microfinance is contributing to the development of the financial system there may be some endogeneity between bank credit and GLP per capita. We will return to this later in the analysis.

This analysis also tests additional control variables not considered in previous studies. Factors such as population density, agricultural land, and government expenditure on education may not only be related to the level of poverty in a country, but may also play a role in the level of outreach or performance of microfinance in a country. For example, according to Alimukhamedova (2014), MFIs are found to have better outreach in countries where population density is high (p. 22). Ahlin et al. (2011) find that a larger agriculture sector predicts significantly lower default rates, operating costs and interest rates among MFIs, while a larger service sector predicts faster MFI growth (Ahlin et al., 2011 as cited in Alimukhamedova, 2014. p. 65).

# 5. Results/Findings

## 5.1. Limited Specification

To examine the findings of Imai et al. (2012) and Miled and Rejeb (2015), the effect of GLP per capita on poverty was estimated controlling for some of the same variables used in these authors’ analyses—GLP per capita, GDP per capita, and domestic credit of banks as a share of GDP. FE/RE estimations were performed for the poverty headcount ratio at $1.90/day and $3.10/day (4 regressions) and for the poverty gap at $1.90/day and $3.10/day (4 regressions), for a total of 8 regressions. Table 4 provides summary statistics of the variables included in the limited specification. The sample consists of 438 observations across 70 countries in the following income categories: low-income, lower middle-income, and upper middle-income.[[13]](#footnote-13) The years covered in the sample are 1999-2014. There are observations for 7 countries for the year 1999 and 24 for the year 2014. The year 2005 has the highest number of countries with observations (38 countries) (see Appendix A). The average poverty headcount ratio across the sample is 14.9% [29.2%] (the percentage of the population living on less than $1.90/day [or $3.10/day]). The average poverty gap is 5.5% [11.9%] (the mean shortfall in income or consumption from the $1.90 [or $3.10] a day mark as a % of the poverty line). Across the sample the average GLP per capita is $41, the average GDP per capita is $7.8K, and the average share of domestic credit by banks to GDP is 31.2%.

Table 4. Summary Statistics of Variables Included in Limited Specification

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Variable** | **# of**  **Obs** | **# of Countries** | **Mean** | **Median** | **Std. Dev.** | **Min.** | **Max** |
| **Poverty** |  |  |  |  |  |  |  |
| Poverty HC Ratio ($1.90/day) | 438 | 70 | 14.905 | 8.010 | 18.615 | 0.000 | 94.050 |
| Poverty HC Ratio ($3.10/day) | 438 | 70 | 29.235 | 21.020 | 25.260 | 0.000 | 98.350 |
| Poverty Gap ($1.90/day) | 438 | 70 | 5.476 | 2.570 | 8.449 | 0.000 | 63.590 |
| Poverty Gap ($3.10/day) | 438 | 70 | 11.949 | 7.265 | 13.427 | 0.000 | 76.400 |
| **Microfinance** |  |  |  |  |  |  |  |
| GLP Per Capita: Sum | 438 | 70 | 41.209 | 12.855 | 78.700 | 0.020 | 628.170 |
| Log GLP Per Capita: Sum | 438 | 70 | 2.373 | 2.554 | 1.917 | -3.912 | 6.443 |
| **Other Controls** |  |  |  |  |  |  |  |
| GDP Per Capita | 438 | 70 | 7834.634 | 6998.245 | 5177.159 | 520.960 | 24879.380 |
| Log GDP Per Capita | 438 | 70 | 8.705 | 8.853 | 0.794 | 6.256 | 10.122 |
| Domestic Credit by Banks (% of GDP) | 438 | 70 | 31.176 | 27.645 | 20.566 | 1.070 | 135.440 |

Results for FE and RE estimations controlling for GDP per capita and domestic credit as a share of GDP are presented in tables 5-6. For the poverty headcount ratio at $1.90/day, the results show a coefficient estimate of -0.3919 for log of GLP per capita of MFIs using a FE model (statistically significant at the 10% level). This is quite similar to Imai et al.’s (2012) finding of -0.37, although their FE coefficient estimate is not statistically significant. In some cases, these results suggest a weaker relationship between GLP per capita of MFIs and poverty than previous authors have found. For example, using RE models, Imai, et al. (2012) find coefficient estimates of between -0.91 and -1.59 and Miled and Rejeb (2015) find a coefficient estimate of -3.13 for log of GLP per capita of MFIs (p. 1679; p. 709-711). My regression shows a coefficient estimate of just -0.5557. However while the RE model yields statistically significant coefficients, the Hausman statistics favor a FE model over a RE model in this case.

A Hausman specification test compares FE and RE models with the null hypothesis being that the individual effects are uncorrelated with other regressors in the model. If the null hypothesis is rejected, that implies that individual effects are significantly correlated with at least one regressor in the model. In this case, the RE model (which captures individual effects in the error term) is no longer Best Linear Unbiased Estimate (BLUE), and therefore a FE model is preferred. In the FE model individual effects are captured in the intercept and correlation between the intercept and regressors does not violate any Gauss-Markov assumptions, thus the FE model is still BLUE (Park, 2011). In the case of the limited specification, the Hausman statistics (reported in tables 5-6 below) are sufficiently large such that we can reject the null hypothesis and conclude that a FE model is more appropriate than a RE model. Therefore, we will focus on the results of the FE estimation.

The results of the limited specification estimations using FE show a statistically significant relationship between MFIs’ GLP per capita and poverty. The results indicate that, controlling for GDP per capita and domestic credit as a share of GDP, GLP per capita has a significant impact on the poverty headcount ratio at the $1.90/day level but does not have a statistically significant effect at the $3.10/day level. This finding suggests that the anti-poverty effect is largest for the poorest of the poor, which is a group microfinance specifically targets. The coefficient estimate of log of GLP per capita of MFIs is also negative and significant at the 1% level for the poverty gap at $1.90/day, which further supports the conclusion that microfinance is having a bigger impact on the poorest of the poor.

Table 5. Limited Specification Results (Dependent Variable: Poverty HC Ratio)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Dependent Variable** | **Poverty HC Ratio ($1.90/Day)** | | **Poverty HC Ratio ($3.10/Day)** | |
| **Explanatory Variables** | **Fixed Effects** | **Random Effects** | **Fixed Effects** | **Random Effects** |
| Log of GLP per capita (sum) | -0.3919 | -0.5557 | -0.3597 | -0.8748 |
|  | -1.85\*\*\* | -2.76\* | -1.26 | -3.26\* |
| Log of GDP per capita | -22.0529 | -21.7958 | -33.6781 | -28.7431 |
|  | -9.74\* | -15.76\* | -11.02\* | -17.90\* |
| Domestic Credit | 0.0556 | 0.0507 | -0.0232 | -0.0324 |
|  | 1.53 | 1.62 | -0.47 | -0.81 |
| Constant | 206.0691 | 205.0659 | 323.9782 | 282.5320 |
|  | 10.94\* | 18.55\* | 12.74\* | 22.05\* |
|  |  |  |  |  |
| Sigma u | 12.8375 | 11.0886 | 14.9455 | 11.6369 |
| Sigma e | 4.8590 | 4.8590 | 6.5587 | 6.5587 |
| Rho | 0.8747 | 0.8389 | 0.8385 | 0.7589 |
|  |  |  |  |  |
| N-Obs | 438 | 438 | 438 | 438 |
| N-Groups | 70 | 70 | 70 | 70 |
| Hausman | - | 185.51 (0.00) | - | 86.45 (0.00) |
| Theta (Median) | - | 0.8077 | - | 0.7556 |
| R2 (Within) | 0.3555 | 0.3546 | 0.4534 | 0.4474 |
| R2 (Between) | 0.7275 | 0.7330 | 0.7830 | 0.7948 |
| R2 (Overall) | 0.6140 | 0.6204 | 0.6709 | 0.6848 |
| F-Statistic/Wald Chi2 (Model) | 67.11 | 414.76 | 100.92 | 594.92 |

Notes: t/z values below coefficients \*, \*\*, and \*\*\* denote significance at 1%, 5%, and 10%, respectively.

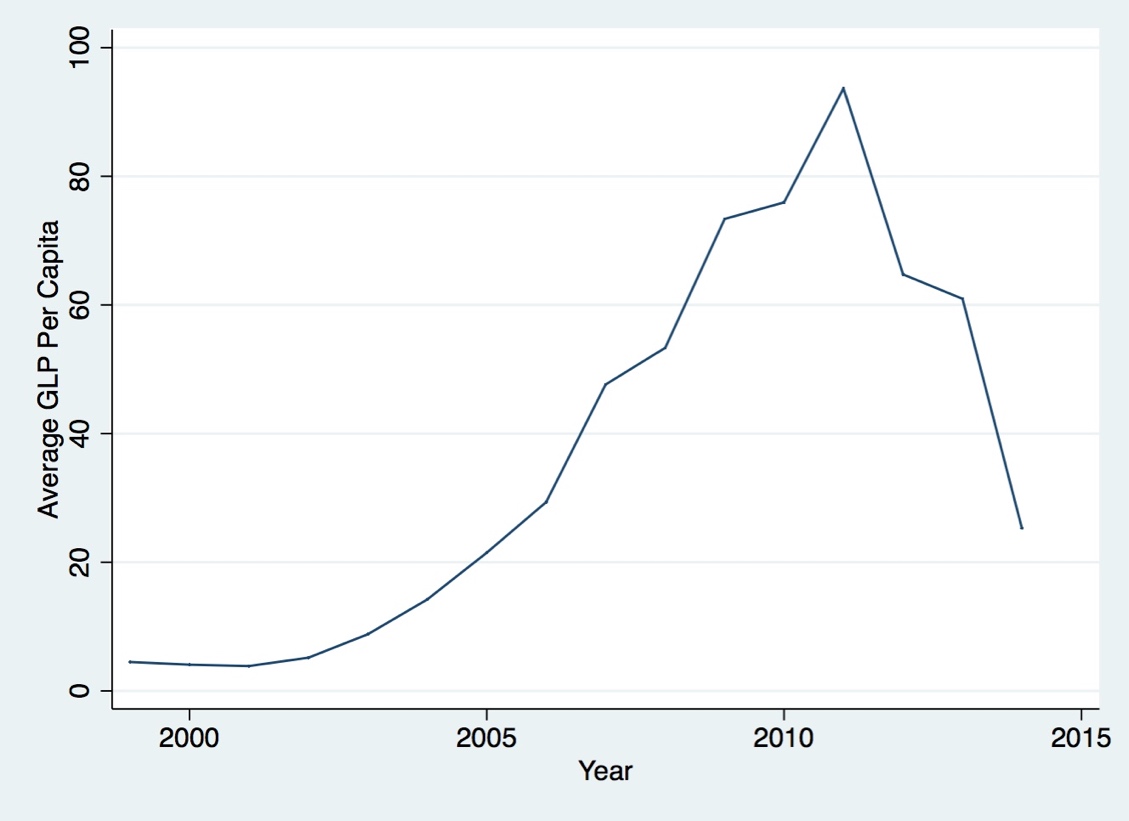
Table 6. Limited Specification Results (Dependent Variable: Poverty Gap)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Dependent Variable** | **Poverty Gap ($1.90/Day)** | | **Poverty Gap ($3.10/Day)** | |
| **Explanatory Variables** | **Fixed Effects** | **Random Effects** | **Fixed Effects** | **Random Effects** |
| Log of GLP per capita (sum) | -0.3283 | -0.3665 | -0.3457 | -0.4915 |
|  | -2.90\* | -3.41\* | -2.27\*\* | -3.40\* |
| Log of GDP per capita | -9.0482 | -9.2188 | -16.7023 | -15.8428 |
|  | -7.50\* | -11.91\* | -10.27\* | -16.31\* |
| Domestic Credit | 0.0535 | 0.0483 | 0.0403 | 0.0320 |
|  | 2.76\* | 2.87\* | 1.54 | 1.44 |
| Constant | 83.3515 | 85.2786 | 156.9047 | 150.2503 |
|  | 8.30\* | 13.77\* | 11.59\* | 19.36\* |
|  |  |  |  |  |
| Sigma u | 7.2195 | 6.5091 | 8.9144 | 7.6728 |
| Sigma e | 2.5903 | 2.5903 | 3.4914 | 3.4914 |
| Rho | 0.8860 | 0.8633 | 0.8670 | 0.8285 |
|  |  |  |  |  |
| N-Obs | 438 | 438 | 438 | 438 |
| N-Groups | 70 | 70 | 70 | 70 |
| Hausman | - | 35.84 (0.00) | - | 104.16 (0.00) |
| Theta (Median) | - | 0.8248 | - | 0.8006 |
| R2 (Within) | 0.2469 | 0.2465 | 0.3890 | 0.3874 |
| R2 (Between) | 0.6112 | 0.6158 | 0.7399 | 0.7472 |
| R2 (Overall) | 0.5044 | 0.5084 | 0.6349 | 0.6434 |
| F-Statistic/Wald Chi2 (Model) | 39.89 | 237.71 | 77.46 | 461.25 |

Notes: t/z values below coefficients \*, \*\*, and \*\*\* denote significance at 1%, 5%, and 10%, respectively.

Specifically, the results show that a 10 percent increase in GLP per capita reduces the poverty headcount ratio at $1.90/day by 0.039 percentage points and reduces the poverty gap by .033 percentage points. To put that in context, the average poverty headcount ratio across the sample is 14.905% and the average poverty gap is 5.476% (at $1.90/day). This means that an increase in MFIs’ GLP per capita of 10 percent would reduce the percentage of the population living on less than $1.90/day from 14.905% to 14.866% and would reduce the poverty gap from 5.476% to 5.443%. While the effect on poverty appears modest, a 10 percent increase in GLP per capita might also be a modest amount in net terms (the average GLP per capita in the sample is just $41). During the 2002-2011 period of growth, the average GLP per capita among the sample expanded from around $4-$5 in 1999-2002 to a peak of $93.65 in 2011, an average increase of 38% per year (see Figure 3 below). The regression results suggest that an annual 38% increase in GLP per capita would cause an annual decrease of approximately 0.15 percentage points in the average poverty rate, and that the total increase in GLP per capita between 2002 and 2011 led to a reduction in the poverty headcount ratio at $1.90/day of approximately 1.35 percentage points over the entire time-period.

Figure 3. Average GLP Per Capita by Year (Limited Specification Sample)



## 5.2. Extensions & Sensitivity Analysis

To extend the analysis beyond the limited framework, a number of other factors have been explored. First, the role of bank/MFI credit is considered. Then we turn to possible differences in the impact of GLP per capita on poverty for countries at different income levels. Next the limited specification is estimated using data restricted to observations in the years 2002-onward. Finally, we consider whether other indicators of microfinance activity and other control variables enhance the limited model.

Because the Hausman statistics in our preliminary analysis (the limited specification) suggest that a fixed effects specification is preferable to a random effects specification, the following discussion focuses only on results from the fixed-effects specification (unless specifically noted otherwise). Results from random effects estimations are available by request.

### 5.2.1. MFI/Bank Credit (Limited Specification)

As discussed previously, one of the ways that microfinance may impact poverty is by contributing to overall financial development. If this is how microfinance has its primary macro effect on poverty, then the effect of gross loan portfolio might be muted by including domestic credit of banks in the model. To consider this, the limited specification regressions were estimated with domestic credit alone, with MFI credit alone, and with both variables included in the model. Donou-Adonsou and Sylwester (2016) also test the effect of bank credit/MFI credit on poverty individually and with both variables included in the same model. They find no statistically significant effect of MFI credit on poverty regardless of whether or not bank credit is included (p. 82, 89). The results of this study are contrary to that.

Overall, for both the dependent variables—poverty headcount ratio and poverty gap—most parameters are little changed when comparing regression results with and without domestic credit as a share of GDP included in the model. Particularly, for the variable of interest, GLP per capita, the coefficient estimates and significance are very similar with and without domestic credit of banks. For example, for the poverty headcount ratio at $1.90/day, GLP per capita is significant at the 10 percent level with and without domestic credit. The coefficient estimate of log of GLP per capita is -0.3919 with domestic credit included in the model and is -0.3849 without domestic credit (see Table C1 in Appendix C). Similarly, for the poverty gap at $1.90/day, log of GLP per capita is significant at the 1 percent level whether or not domestic credit of banks is included in the model and the coefficient estimates differ by just 0.015 (see Table C2 in Appendix C).

### 5.2.2. Income Groups (Limited Specification)

Microfinance is generally aimed at serving low-income clients and communities without access to traditional banking. Therefore, it is possible that the impact of microfinance would be different in lower income countries compared to higher income countries with relatively more developed financial sectors and greater access to financial services across the population. To explore this, the sample was divided into 3 different income groups: upper middle-income, lower middle-income, and low-income. Countries were assigned an income group according to the World Bank’s classification of countries by income as of March 2017 (World Bank, World Bank Country and Lending Groups).

The limited specification outlined above, which controls for GLP per capita, GDP per capita, and domestic credit of banks as a % of GDP, was tested for each of the 3 income groups. Restricting the sample to only low-income countries resulted in too few observations to yield meaningful results (just 45 observations for the low-income group). Because of this, the countries were also grouped into two broader income groups: 1. “upper middle-income” (consisting of upper middle-income countries), and 2. “lower-income” (consisting of low-income and lower middle-income countries).

Table 7. Limited Specification: Number of Observations by Income Group

|  |  |
| --- | --- |
| **Income Group** | **# of Observations** |
| *Upper Middle-Income* | *208* |
| *Lower-Income* | *230* |

Comparing regression results for the upper middle-income countries and lower-income countries separately, reveals a few important things. Notably, the impact of GLP per capita on the poverty headcount ratio ($1.90/day) is larger for the sample of “lower-income” countries, which might be expected given the focus of microfinance on poor individuals and communities. For lower-income countries, the coefficient estimate of the log of GLP per capita is -0.6198 (statistically significant at the 10% level), suggesting that a 10 percent increase in MFI’s GLP per capita reduces poverty by 0.062 percentage points. For upper middle-income countries, the coefficient estimate is -0.3416 (statistically significant at the 5% level), suggesting a reduction in poverty of 0.034 percentage points for an equivalent increase in GLP per capita. At $3.10/day, GLP per capita does not appear to have a significant impact on the poverty headcount ratio when the sample is restricted to the lower-income countries, but does have a significant effect for the upper middle-income sample (coefficient estimate of -0.510 for log of GLP per capita; significant at the 5% level). This finding further supports the conclusion that microfinance has a greater impact on the poor compared to the near-poor and non-poor.

As expected, the impact of GLP per capita on the poverty gap is larger for the lower-income countries than upper middle-income countries (at both $1.90/day and $3.10/day). The results suggest that a 10 percent increase in GLP per capita reduces the poverty gap at $1.90/day by 0.0209 percentage points for the sample of upper middle-income countries and reduces the poverty gap by 0.0517 percentage points for the sample of lower-income countries (statistically significant at 1% and 5%, respectively). At $3.10/day the impact is slightly larger. The results show that a 10 percent increase in GLP per capita reduces the poverty gap at $3.10/day by 0.0294 percentage points for upper middle-income countries and by 0.0524 percentage points for lower-income countries (statistically significant at 5%). Regression results are presented in tables C3-C4 in Appendix C.

### 5.2.3. Time-Period

Imai et al. (2012) notes that while MIX data date back to 1994, most MFIs were not eager to submit their records for public use until 2002, though the authors provide no source for this statement (p. 1684). Therefore, as another sensitivity test, the limited specification was estimated using data from only 2002 onward to examine whether the sample was significantly different. The results of the impact of MFIs’ GLP per capita on poverty with the sample restricted to observations in 2002-onward are presented in tables C5-C6 in Appendix C. Restricting the sample to the 2002-onward time-period appears to substantially alter the results. In our base estimation using the full sample, the FE estimations showed statistically significant effects of GLP per capita on both the poverty headcount ratio and the poverty gap. Restricting the sample to 2002-ownard results in the effects both being insignificant and of much lower magnitude.

In our base estimation, the FE model yields a coefficient estimate of -0.392 for the impact of log of GLP per capita on the poverty headcount ratio at $1.90/day (statistically significant at the 10% level). In the time-period restricted estimation the FE model does not show a statistically significant effect, and yields a coefficient estimate of just -0.062 for log of GLP per capita, a reduction in magnitude of more than six-fold. For the poverty gap at $1.90/day the base estimation using FE showed a coefficient estimate of the impact of log of GLP per capita of -0.328 (statistically significant at the 1% level). In the time-period restricted sample the equivalent effect is insignificant and reduced to -0.141.

Clearly, this sensitivity test reveals that there are some significant limitations to the findings of this analysis using the base model because it suggests that the results are sensitive to the inclusion/exclusion of certain observations. Furthermore, the sample size is not greatly diminished by restricting the sample to 2002-onward, which suggests that a smaller sample size/fewer degrees of freedom is not a likely cause for the lack of significance.

### 5.2.4. Additional Measures of Microfinance

In addition to gross loan portfolio (GLP) of MFIs, the Microfinance Information Exchange (MIX) reports a number of other microfinance indicators at the country level. GLP per capita is our chosen measure of microfinance activity because it measures the funds distributed to individuals. However it is possible that other aspects of microfinance might be more revealing in terms of the impact of microfinance on poverty at the country level. Therefore, a series of regressions were estimated including various different microfinance indicators. Microfinance variables that were considered include: the number of MFIs in a country, the number of active borrowers, the average loan balance per borrower, the percentage of borrowers that are female, and the average outstanding balance per borrower.

In most cases adding other microfinance indicators to the model resulted in both GLP per capita and the added microfinance indicator becoming insignificant, likely because of high correlation among the microfinance variables. What did emerge is that the number of active women borrowers as a percentage of total borrowers has a statistically significant relationship with poverty. Across the sample, on average women make up a little more than 44 percent of total active borrowers (mean: 0.441; min: 0; max: 0.99). Results of the FE estimation of the limited specification with average percentage of female borrowers added to the model are presented in Table C7 in Appendix C. For the poverty headcount ratio at both $1.90/day and $3.10/day, the results show statistically significant coefficient estimates of -6.4686 and -9.9491, respectively, for the percentage of female borrowers. This suggests that the more represented women are among MFI clients, the greater the impact of MFIs on poverty. This is consistent with the idea that aiming resources to women may deliver stronger development impacts (Armendariz de Aghion and Morduch, 2010. p. 183-184).

In addition to adding other microfinance indicators to the limited specification, the effect of different microfinance indicators in place of GLP per capita was tested. Looking at the number of MFIs as well as GLP per capita might be revealing because while the number of operating MFIs and the total gross loan portfolio are obviously highly correlated, MFIs often offer other services besides loans. Emerging evidence suggests that other products such as micro savings, insurance, and payment services for business transactions or remittances may play an equal or even greater role in influencing poverty (IFC, nd). Table C8 in Appendix C reports the results of the FE estimation of the limited specification with the number of MFIs as the main indicator of microfinance instead of GLP per capita. The results suggest that for each additional MFI operating in a country the poverty headcount ratio is reduced by approximately 0.06 percentage points. The results also suggest that the poverty gap at $1.90/day and $3.10/day is reduced by 0.03 and 0.04 percentage points, respectively, by an additional MFI. In the sample there is an average of 17 MFIs per country (min: 0; max: 122).

### 5.2.5. Additional Control Variables

To expand on previous analyses, additional control variables that might impact a country’s poverty level were considered. This exercise was also aimed at seeing if the impact of MFIs’ GLP per capita is sensitive to the inclusion of additional variables. The effect of GLP per capita on poverty controlling for the variables included in the limited specification (GDP per capita and domestic credit of banks as a % of GDP), as well as additional control variables collected from the World Bank’s World Development Indicators (WDI) is presented in Table C9 in Appendix C. Control variables that were added include: population density, population growth, rural population growth, age dependency ratio, fertility rate, labor force participation rate, employment to population ratio, agricultural land as a % of total land, and agricultural value-added per worker.

Even after the introduction of these variables, MFIs’ GLP per capita appears to have a statistically significant and negative effect on poverty as measured by the poverty headcount ratio and the poverty gap.[[14]](#footnote-14) For the poverty headcount ratio at $1.90 per day, the coefficient of log of GLP per capita is -0.6218 (statistically significant at the 5% level), suggesting that a 10 percent increase in MFIs’ GLP per capita is associated with a reduction in poverty of 0.0622 percentage points. The results suggest that an equivalent increase in GLP per capita reduces the poverty gap at $1.90/day by 0.0418 percentage points. Unlike the findings in previous parts of this analysis, the impact of GLP per capita is not limited to the lower poverty line ($1.90/day), but appears to have a significant effect at both the $1.90/day and $3.10/day mark. The estimated effect of GLP per capita on the poverty headcount ratio in this case is actually slightly larger at the $3.10/day level compared to the $1.90/day level (coefficient of -0.6304 versus -0.6218 for log of GLP per capita).

With respect to the other variables in the model, many showed impacts on poverty that might be expected. GDP per capita, for example, is strongly negatively related to the poverty headcount ratio and the poverty gap and is statistically significant irrespective of the model specification or the poverty line considered. The coefficient estimate for age dependency ratio is positive and statistically significant in most cases, which makes sense since a higher age dependency ratio implies a larger share of dependents to be supported by the working age population. The share of total land devoted to agriculture has a statistically significant negative impact on poverty, which might be expected since agriculture employs a large share of people in many developing countries (World Bank, WDI: Agricultural inputs). As expected, labor force participation is negatively related to poverty, but is not statistically significant. The results suggest that overall population growth is associated with higher levels of poverty headcount ratio, while rural population growth is associated with lower poverty. Greater population density is also associated with lower poverty according to these results. Factors that appear to have no statistically significant impact on poverty according to this estimation include domestic credit of banks to the private sector as a % of GDP and agricultural value added per worker. The model also produced unexpected coefficient signs for several variables. For example, the results indicate that higher fertility rates are associated with lower poverty headcount ratio. However countries with some of the highest fertility rates are also among the poorest, while low-fertility countries tend to be richer (The Economist, 2012). The results also suggest a positive relationship between employment-population ratio and the poverty headcount ratio at $1.90/day, which is counter to what one would expect.

There are a number of limitations to this portion of the analysis. For one, the control variables included could be chosen more carefully. Some of the variables included are likely to be highly correlated (for example, labor force participation rate and employment to population ratio). Also, some important factors that affect poverty are absent from the model, notably education. A more careful model specification would undoubtedly improve the reliability of the results and better estimate the true impact of microfinance as measured by MFIs’ gross loan portfolio per capita. Future work would also benefit from a careful examination of which factors that influence poverty might have unique interactions with microfinance.

# 6. Conclusion

In the past several decades microfinance has gained popularity among policymakers and other stakeholders and there have been concerted efforts to expand microfinance programs with the objective of promoting development and reducing poverty. However studies of the effect of microfinance on poverty have produced mixed results, and the number of studies of the effect on poverty at a macro level is limited. The goal of this project was to add to the evidence base regarding the use of microfinance as a policy tool for combatting poverty on a macro level by both verifying the findings of previous work and enriching the frameworks of previous studies. The project centered on the hypothesis that countries with higher Microfinance Institutions’ (MFIs’) gross loan portfolio (GLP) per capita have lower levels of poverty. Using panel data covering approximately 70 developing countries for the years 1999-2014 and fixed-effects estimation, this analysis found evidence of a statistically significant negative effect of GLP per capita of MFIs on poverty. Previous analysis by Imai, et al. (2012) only found statistically significant results using a random-effects estimation.

The results of this analysis indicate that, controlling for GDP per capita and domestic credit as a share of GDP, GLP per capita has a significant impact on the poverty headcount ratio at the $1.90/day level but does not have a statistically significant effect at the $3.10/day level. This finding suggests that the anti-poverty effect is largest for the poorest of the poor, which is a group microfinance specifically targets. The results also show a statistically significant relationship between GLP per capita of MFIs and the poverty gap, which further supports the conclusion that microfinance has a bigger impact on the poorest of the poor. Specifically, the results show that a 10 percent increase in GLP per capita reduces the poverty headcount ratio at $1.90/day by 0.039 percentage points and reduces the poverty gap by .033 percentage points. While the effect on poverty appears modest, a 10 percent increase in GLP per capita might also be a modest amount in net terms. During the 2002-2011 period the average GLP per capita among the sample grew from around $4-$5 in 1999-2002 to a peak of $93.65 in 2011, an average increase of 38% per year. The regression results suggest that an annual 38% increase in GLP per capita would cause an annual decrease of approximately 0.15 percentage points in the average poverty rate, and that the total increase in GLP per capita between 2002 and 2011 led to a reduction in the poverty headcount ratio at $1.90/day of approximately 1.35 percentage points over the entire time-period.

This project also explored other aspects of the relationship between microfinance and poverty, including the role of MFI/bank credit, possible differences in the impact of GLP per capita on poverty for countries at different income levels, and the effect of restricting the sample to the 2002-onward time-period. The effect of other measures of microfinance activity on poverty and the inclusion of additional control variables was also tested. A few notable findings of these exercises are related to the impact of MFIs’ GLP per capita for countries at different income levels and the impact of female participation in microfinance. Analysis of countries at different income levels revealed that GLP per capita has a larger anti-poverty effect in low-income and lower middle-income countries compared to upper middle-income countries. The analysis also found that there is a significant relationship between higher percentages of female microfinance borrowers and lower poverty, a factor not explored in previous studies by Imai, et al. (2012), Miled and Rejeb (2015), and Donou-Adonsou and Sylwester (2016).

While the results of this project support the conclusion that microfinance can contribute to poverty reduction—in terms of both incidence and depth—there are limitations to this analysis that could be improved/refined in future work to gain a better understanding of the true impact of microfinance. As more evaluations of the impact of microfinance on poverty on a macro-level are conducted, research could also be extended to explore other aspects of the relationship. A few areas of interest are: whether microfinance has different effects on poverty in urban versus rural settings; whether there is any relationship between movements in poverty overtime and specific use of micro-loans (e.g., for consumption vs. productive purposes); and the effect of other microfinance products such as micro savings, insurance, and payment services for business transactions. Furthermore, continuing technological and institutional innovations suggest that the microfinance industry will continue to grow as new methods of delivery and service models emerge (IFC, nd), heightening the importance of understanding microfinance’s effects and creating new areas for research.

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# Variable Definitions & Notes

*Microfinance Information Exchange Data*

|  |  |
| --- | --- |
| **Indicator** | **Definition** |
| Gross Loan Portfolio | All outstanding principals due for all outstanding client loans. This includes current, delinquent, and renegotiated loans, but not loans that have been written off. It does not include interest receivable. |
| Percent of female borrowers | Number of active women borrowers as a percentage of total borrowers at period end. Calculated as the number of active female borrowers/number of active borrowers |
| Number of Active Borrowers | The number of individuals or entities who currently have an outstanding loan balance with the MFI or are primarily responsible for repaying any portion of the Loan Portfolio, Gross. Individuals who have multiple loans with an MFI should be counted as a single borrower. |
| Average Loan Balance per Borrower | Gross Loan Portfolio / Number of Active Borrowers. |
| Average Outstanding Balance | Gross Loan Portfolio / Number of Loans Outstanding. |

Source: Microfinance Information Exchange, Inc. *Glossary*. <https://www.themix.org/resource/glossary/glossary>.

*World Bank (WB) Indicators*

| **Indicator Name** | **Long definition** | **WB Source** |
| --- | --- | --- |
| Poverty headcount ratio at $1.90 a day (2011 PPP) (% of population) | Poverty headcount ratio at $1.90 a day is the percentage of the population living on less than $1.90 a day at 2011 international prices. As a result of revisions in PPP exchange rates, poverty rates for individual countries cannot be compared with poverty rates reported in earlier editions. | [1] |
| Poverty headcount ratio at $3.10 a day (2011 PPP) (% of population) | Poverty headcount ratio at $3.10 a day is the percentage of the population living on less than $3.10 a day at 2011 international prices. As a result of revisions in PPP exchange rates, poverty rates for individual countries cannot be compared with poverty rates reported in earlier editions. | [1] |
| Poverty gap at $1.90 a day (2011 PPP) (%) | Poverty gap at $1.90 a day (2011 PPP) is the mean shortfall in income or consumption from the poverty line $1.90 a day (counting the nonpoor as having zero shortfall), expressed as a percentage of the poverty line. This measure reflects the depth of poverty as well as its incidence. As a result of revisions in PPP exchange rates, poverty rates for individual countries cannot be compared with poverty rates reported in earlier editions. | [1] |
| Poverty gap at $3.10 a day (2011 PPP) (%) | Poverty gap at $3.10 a day (2011 PPP) is the mean shortfall in income or consumption from the poverty line $3.10 a day (counting the nonpoor as having zero shortfall), expressed as a percentage of the poverty line. This measure reflects the depth of poverty as well as its incidence. As a result of revisions in PPP exchange rates, poverty rates for individual countries cannot be compared with poverty rates reported in earlier editions. Note: five countries -- Bangladesh, Cabo Verde, Cambodia, Jordan, and Lao PDR -- use the 2005 PPP conversion factors and corresponding $1.25 a day and $2 a day poverty lines. This is due to the large deviations in the rate of change in PPP factors relative to the rate of change in domestic consumer price indexes. See Box 1.1 in the Global Monitoring Report 2015/2016 (http://www.worldbank.org/en/publication/global-monitoring-report) for a detailed explanation. | [1] |
| GDP per capita, PPP (constant 2011 international $) | GDP per capita based on purchasing power parity (PPP). PPP GDP is gross domestic product converted to international dollars using purchasing power parity rates. An international dollar has the same purchasing power over GDP as the U.S. dollar has in the United States. GDP at purchaser's prices is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Data are in constant 2011 international dollars. | [3] |
| Domestic credit to private sector by banks (% of GDP) | Domestic credit to private sector by banks refers to financial resources provided to the private sector by other depository corporations (deposit taking corporations except central banks), such as through loans, purchases of nonequity securities, and trade credits and other accounts receivable, that establish a claim for repayment. For some countries these claims include credit to public enterprises. | [4] |
| Population density (people per sq. km of land area) | Population density is midyear population divided by land area in square kilometers. Population is based on the de facto definition of population, which counts all residents regardless of legal status or citizenship--except for refugees not permanently settled in the country of asylum, who are generally considered part of the population of their country of origin. Land area is a country's total area, excluding area under inland water bodies, national claims to continental shelf, and exclusive economic zones. In most cases the definition of inland water bodies includes major rivers and lakes. | [5] |
| Population growth (annual %) | Annual population growth rate for year t is the exponential rate of growth of midyear population from year t-1 to t, expressed as a percentage. Population is based on the de facto definition of population, which counts all residents regardless of legal status or citizenship--except for refugees not permanently settled in the country of asylum, who are generally considered part of the population of the country of origin. | [6] |
| Rural population growth (annual %) | Rural population refers to people living in rural areas as defined by national statistical offices. It is calculated as the difference between total population and urban population. | [7] |
| Age dependency ratio (% of working-age population) | Age dependency ratio is the ratio of dependents--people younger than 15 or older than 64--to the working-age population--those ages 15-64. Data are shown as the proportion of dependents per 100 working-age population. | [8] |
| Fertility rate, total (births per woman) | Total fertility rate represents the number of children that would be born to a woman if she were to live to the end of her childbearing years and bear children in accordance with current age-specific fertility rates. | [9] |
| Labor force participation rate (%) | Labor force participation rate is the proportion of the population ages 15 and older that is economically active: all people who supply labor for the production of goods and services during a specified period. | [10] |
| Employment to population ratio (%) | Employment to population ratio is the proportion of a country's population that is employed. Ages 15 and older are generally considered the working-age population. | [10] |
| Agricultural land (% of land area) | Agricultural land refers to the share of land area that is arable, under permanent crops, and under permanent pastures. Arable land includes land defined by the FAO as land under temporary crops (double-cropped areas are counted once), temporary meadows for mowing or for pasture, land under market or kitchen gardens, and land temporarily fallow. Land abandoned as a result of shifting cultivation is excluded. Land under permanent crops is land cultivated with crops that occupy the land for long periods and need not be replanted after each harvest, such as cocoa, coffee, and rubber. This category includes land under flowering shrubs, fruit trees, nut trees, and vines, but excludes land under trees grown for wood or timber. Permanent pasture is land used for five or more years for forage, including natural and cultivated crops. FAO: Food and Agriculture Organization. | [11] |
| Agriculture value added per worker (constant 2010 US$) | Agriculture value added per worker is a measure of agricultural productivity. Value added in agriculture measures the output of the agricultural sector (ISIC divisions 1-5) less the value of intermediate inputs. Agriculture comprises value added from forestry, hunting, and fishing as well as cultivation of crops and livestock production. Data are in constant 2010 US$. | [12] |
| Government expenditure on education, total (% of GDP) | General government expenditure on education (current, capital, and transfers) expressed as a percentage of GDP. Includes expenditure funded by transfers from international sources to government. General government usually refers to local, regional and central governments. | [13] |

World Bank Sources:

[1] World Bank, Development Research Group. Data are based on primary household survey data obtained from government statistical agencies and World Bank country departments. Data for high-income economies are from the Luxembourg Income Study database. For more information and methodology, please see PovcalNet (<http://iresearch.worldbank.org/PovcalNet/index.htm)>.

[2] The World Bank. PovcalNet. *PovcalNet: an online analysis tool for global poverty monitoring.* <http://iresearch.worldbank.org/PovcalNet/index.htm>.

[3] World Bank, International Comparison Program database.

[4] International Monetary Fund, International Financial Statistics and data files, and World Bank and OECD GDP estimates.

[5] Food and Agriculture Organization and World Bank population estimates.

[6] Derived from total population. Population source: (1) United Nations Population Division. World Population Prospects, (2) United Nations Statistical Division. Population and Vital Statistics Report (various years), (3) Census reports and other statistical publications from national statistical offices, (4) Eurostat: Demographic Statistics, (5) Secretariat of the Pacific Community: Statistics and Demography Programme, and (6) U.S. Census Bureau: International Database.

[7] World Bank Staff estimates based on United Nations, World Urbanization Prospects.

[8] World Bank staff estimates from various sources including census reports, the United Nations Population Division's World Population Prospects, national statistical offices, household surveys conducted by national agencies, and ICF International.

[9] (1) United Nations Population Division. World Population Prospects, (2) United Nations Statistical Division. Population and Vital Statistics Report (various years), (3) Census reports and other statistical publications from national statistical offices, (4) Eurostat: Demographic Statistics, (5) Secretariat of the Pacific Community: Statistics and Demography Programme, and (6) U.S. Census Bureau: International Database.

[10] International Labour Organization, Key Indicators of the Labour Market database.

[11] Food and Agriculture Organization, electronic files and web site.

[12] Derived from World Bank national accounts files and Food and Agriculture Organization, Production Yearbook and data files.

[13] United Nations Educational, Scientific, and Cultural Organization (UNESCO) Institute for Statistics.

# Appendix A. Panel Data: Countries & Years

Table A1. Unbalanced Panel for Limited Specification

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Poverty Headcount Ratio/Poverty Gap** | | | | |
| **Year** | **# of Countries** | **Year** | **# of Countries** |
| 1999 | 7 | 2007 | 31 |
| 2000 | 14 | 2008 | 31 |
| 2001 | 19 | 2009 | 34 |
| 2002 | 24 | 2010 | 31 |
| 2003 | 29 | 2011 | 35 |
| 2004 | 34 | 2012 | 31 |
| 2005 | 38 | 2013 | 22 |
| 2006 | 34 | 2014 | 24 |
|  |  | **Total** | **438** |

Table A2. List of Countries for Panel Data (Limited Specification)

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Country** | **Income Group** | **Freq.** | **Country** | **Income Group** | **Freq.** |
| Albania | UMI | 4 | Macedonia, FYR | UMI | 5 |
| Armenia | LMI | 13 | Madagascar | LI | 5 |
| Azerbaijan | UMI | 5 | Malawi | LI | 2 |
| Bangladesh | LMI | 3 | Mali | LI | 3 |
| Benin | LI | 2 | Mexico | UMI | 9 |
| Bolivia | LMI | 12 | Moldova | LMI | 11 |
| Bosnia and Herzegovina | UMI | 4 | Mongolia | LMI | 6 |
| Brazil | UMI | 13 | Morocco | LMI | 2 |
| Bulgaria | UMI | 9 | Mozambique | LI | 2 |
| Burkina Faso | LI | 3 | Nepal | LI | 2 |
| Burundi | LI | 1 | Nicaragua | LMI | 4 |
| Cambodia | LMI | 6 | Niger | LI | 4 |
| Cameroon | LMI | 3 | Nigeria | LMI | 2 |
| People's Republic of China | UMI | 5 | Pakistan | LMI | 7 |
| Colombia | UMI | 14 | Palestine/West Bank and Gaza | LMI | 5 |
| Democratic Republic of the Congo | LI | 2 | Panama | UMI | 11 |
| Republic of the Congo | LMI | 1 | Paraguay | UMI | 14 |
| Costa Rica | UMI | 12 | Peru | UMI | 15 |
| Cote d'Ivoire (Ivory Coast) | LMI | 2 | Philippines | LMI | 5 |
| Dominican Republic | UMI | 12 | Romania | UMI | 12 |
| Ecuador | UMI | 14 | Russia/Russian Federation | UMI | 12 |
| El Salvador | LMI | 14 | Rwanda | LI | 1 |
| Ethiopia | LI | 1 | Senegal | LI | 3 |
| Georgia | UMI | 13 | Serbia | UMI | 10 |
| Ghana | LMI | 1 | Sierra Leone | LI | 1 |
| Guatemala | LMI | 5 | South Africa | UMI | 4 |
| Guinea | LI | 1 | Sri Lanka | LMI | 4 |
| Haiti | LI | 2 | Sudan | LMI | 1 |
| Honduras | LMI | 15 | Tajikistan | LMI | 7 |
| India | LMI | 3 | Tanzania | LI | 3 |
| Indonesia | LMI | 15 | Togo | LI | 2 |
| Kazakhstan | UMI | 11 | Uganda | LI | 5 |
| Kenya | LMI | 1 | Ukraine | LMI | 4 |
| Kosovo | LMI | 8 | Vietnam | LMI | 6 |
| Kyrgyzstan/Kyrgyz Republic | LMI | 15 | Zambia | LMI | 4 |
| **Total** | | | | | **438** |

LI: Low Income LMI: Lower Middle Income UMI: Upper Middle Income

# Appendix B. Additional Summary Statistics & Figures

Table B1. Correlation Matrix (Limited Specification Sample)

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Variable** | Pov HC  $1.9 | Pov Gap  $1.9 | Pov HC  $3.1 | Pov Gap $3.1 | Log GLP/ Cap (Sum) | Log GDP/  Cap | Domestic Credit |
| Pov HC $1.9 | 1.00 |  |  |  |  |  |  |
| Pov Gap $1.9 | 0.9565\* | 1.00 |  |  |  |  |  |
| Pov HC $3.1 | 0.9332\* | 0.8143\* | 1.00 |  |  |  |  |
| Pov Gap $3.1 | 0.9965\* | 0.9543\* | 0.9487\* | 1.00 |  |  |  |
| Log GLP/Capita (Sum) | -0.4531\* | -0.4299\* | -0.4387\* | -0.4573\* | 1.00 |  |  |
| Log GDP/Capita | -0.7739\* | -0.6949\* | -0.8136\* | -0.7857\* | 0.2621\* | 1.00 |  |
| Domestic Credit | -0.3281\* | -0.2900\* | -0.3603\* | -0.3361\* | 0.1568\* | 0.4378\* | 1.00 |

\*, \*\*, and \*\*\* denote significance at 1%, 5%, and 10%, respectively.

Figure B1. Distribution of Log of GLP Per Capita

(Limited Specification Sample)

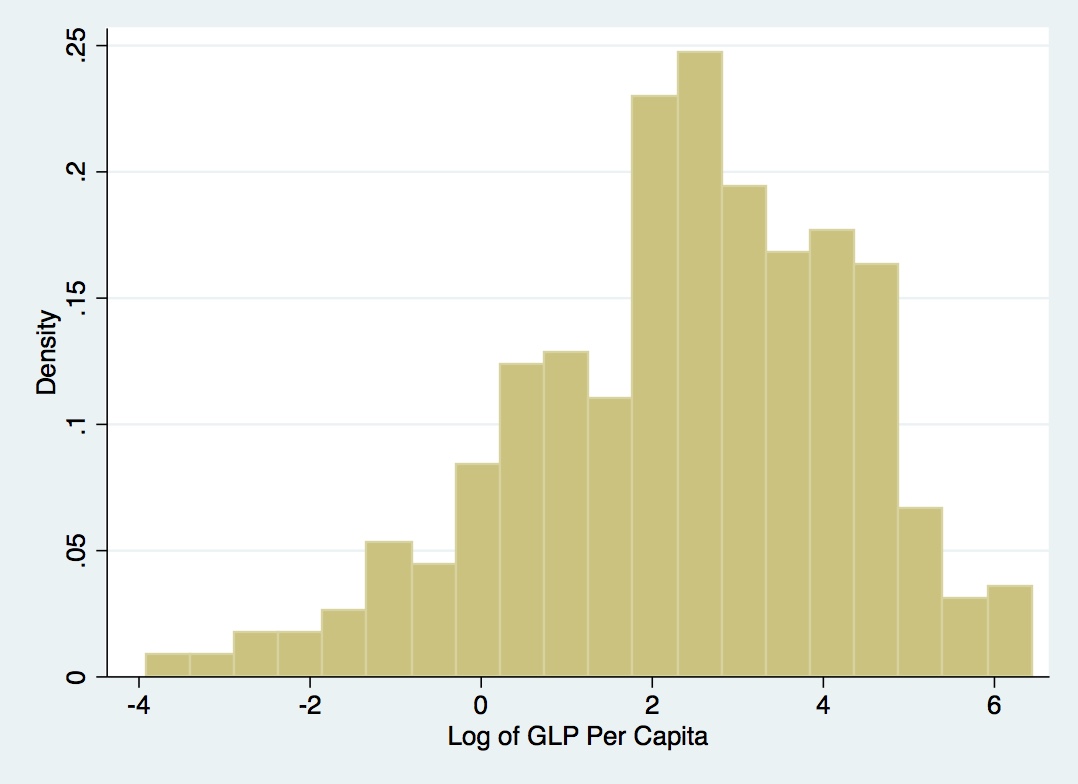


Figure B2. GLP Per Capita v. GDP Per Capita (Limited Specification Sample)

|  |  |
| --- | --- |
|  |  |

# Appendix C. Regression Results

## **MFI/Bank Credit**

Table C1. Limited Specification Results: MFI/Bank Credit (Dependent Variable: Poverty HC Ratio) [Fixed Effects Model]

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Dependent Variable** | **Poverty HC Ratio ($1.90/Day)** | | | **Poverty HC Ratio ($3.10/Day)** | | |
| **Explanatory Variables** | **MFI Credit & Bank Credit** | **MFI Credit Only** | **Bank Credit Only** | **MFI Credit & Bank Credit** | **MFI Credit Only** | **Bank Credit Only** |
| Log of GLP per capita (sum) | -0.3919 | -0.3849 | - | -0.3597 | -0.3896 | - |
|  | -1.85\*\*\* | -1.83\*\*\* | - | -1.26 | -1.37 | - |
| Log of GDP per capita | -22.0529 | -19.7695 | -22.6038 | -33.6781 | -33.9781 | -35.9803 |
|  | -9.74\* | -11.18\* | -15.22\* | -11.02\* | -14.24\* | -18.31\* |
| Domestic Credit | 0.0556 | - | 0.0249 | -0.0232 | - | -0.0648 |
|  | 1.53 | - | 0.90 | -0.47 | - | -1.78\*\*\* |
| Constant | 206.0691 | 188.1023 | 211.4232 | 323.9782 | 326.0594 | 345.1033 |
|  | 10.94\* | 12.43\* | 17.02\* | 12.74\* | 15.97\* | 21.00\* |
|  |  |  |  |  |  |  |
| Sigma u | 12.8375 | 13.1071 | 12.7695 | 14.9455 | 14.9452 | 17.1505 |
| Sigma e | 4.8590 | 4.8435 | 5.1401 | 6.5587 | 6.5322 | 6.8013 |
| Rho | 0.8747 | 0.8799 | 0.8606 | 0.8385 | 0.8396 | 0.8641 |
|  |  |  |  |  |  |  |
| N-Obs | 438 | 446 | 589 | 438 | 446 | 589 |
| N-Groups | 70 | 73 | 97 | 70 | 73 | 97 |
| R2 (Within) | 0.3555 | 0.3512 | 0.4213 | 0.4534 | 0.4493 | 0.5622 |
| R2 (Between) | 0.7275 | 0.7269 | 0.7143 | 0.7830 | 0.7796 | 0.7545 |
| R2 (Overall) | 0.6140 | 0.6198 | 0.6237 | 0.6709 | 0.6788 | 0.6829 |
| F-Statistic/Wald Chi2 (Model) | 67.11 | 100.41 | 178.35 | 100.92 | 151.33 | 314.62 |

Table C2. Limited Specification Results: MFI/Bank Credit (Dependent Variable: Poverty Gap) [FE Model]

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Dependent Variable** | **Poverty Gap ($1.90/Day)** | | | **Poverty Gap ($3.10/Day)** | | |
| **Explanatory Variables** | **MFI Credit & Bank Credit** | **MFI Credit Only** | **Bank Credit Only** | **MFI Credit & Bank Credit** | **MFI Credit Only** | **Bank Credit Only** |
| Log of GLP per capita (sum) | -0.3283 | -0.3132 | - | -0.3457 | -0.3417 | - |
|  | -2.90\* | -2.76\* | - | -2.27\*\* | -2.26\*\* | - |
| Log of GDP per capita | -9.0482 | -7.0425 | -9.2724 | -16.7023 | -15.0271 | -17.3483 |
|  | -7.50\* | -7.38\* | -12.38\* | -10.27\* | -11.81\* | -16.55\* |
| Domestic Credit | 0.0535 | - | 0.0396 | 0.0403 | - | 0.0167 |
|  | 2.76\* | - | 2.86\* | 1.54 | - | 0.86 |
| Constant | 83.3515 | 67.5864 | 85.1837 | 156.9047 | 143.6733 | 162.8258 |
|  | 8.30\* | 8.28\* | 13.60\* | 11.59\* | 13.19\* | 18.57\* |
|  |  |  |  |  |  |  |
| Sigma u | 7.2195 | 7.2150 | 7.1689 | 8.9144 | 8.8672 | 9.2671 |
| Sigma e | 2.5903 | 2.6123 | 2.5919 | 3.4914 | 3.4849 | 3.6289 |
| Rho | 0.8860 | 0.8841 | 0.8844 | 0.8670 | 0.8662 | 0.8670 |
|  |  |  |  |  |  |  |
| N-Obs | 438 | 446 | 589 | 438 | 446 | 589 |
| N-Groups | 70 | 73 | 97 | 70 | 73 | 97 |
| R2 (Within) | 0.2469 | 0.2313 | 0.2834 | 0.3890 | 0.3840 | 0.4647 |
| R2 (Between) | 0.6112 | 0.6384 | 0.5838 | 0.7399 | 0.7443 | 0.7136 |
| R2 (Overall) | 0.5044 | 0.5213 | 0.4939 | 0.6349 | 0.6428 | 0.6376 |
| F-Statistic/Wald Chi2 (Model) | 39.89 | 55.80 | 96.92 | 77.46 | 115.61 | 212.73 |

Notes: t/z values below coefficients \*, \*\*, and \*\*\* denote significance at 1%, 5%, and 10%, respectively.

## **Income Groups**

Table C3. Limited Specification Results: Income Groups (Dependent Variable: Poverty HC Ratio) [FE Model]

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Dependent Variable** | **Poverty HC Ratio ($1.90/Day)** | | **Poverty HC Ratio ($3.10/Day)** | |
| **Explanatory Variables** | **UMI** | **LI & LMI** | **UMI** | **LI & LMI** |
| Log of GLP per capita (sum) | -0.3416 | -0.6198 | -0.5100 | -0.4343 |
|  | -2.08\*\* | -1.67\*\*\* | -1.99\*\* | -0.90 |
| Log of GDP per capita | -12.6667 | -31.6574 | -20.9490 | -46.4870 |
|  | -7.14\* | -8.09\* | -7.59\* | -9.12\* |
| Domestic Credit | 0.0393 | 0.0280 | -0.0250 | -0.0865 |
|  | 1.46 | 0.41 | -0.60 | -0.98 |
| Constant | 123.5303 | 281.7870 | 211.5809 | 425.3395 |
|  | 7.85\* | 9.20\* | 8.64\* | 10.65\* |
|  |  |  |  |  |
| Sigma u | 5.8626 | 13.8739 | 11.3013 | 19.3544 |
| Sigma e | 2.6960 | 5.9235 | 4.1945 | 7.7234 |
| Rho | 0.8254 | 0.8458 | 0.8789 | 0.8626 |
|  |  |  |  |  |
| N-Obs | 208 | 230 | 208 | 230 |
| N-Groups | 21 | 49 | 21 | 49 |
| R2 (Within) | 0.4110 | 0.4374 | 0.5119 | 0.5194 |
| R2 (Between) | 0.1319 | 0.7009 | 0.0809 | 0.7068 |
| R2 (Overall) | 0.3345 | 0.6283 | 0.3284 | 0.5832 |
| F-Statistic/Wald Chi2 (Model) | 42.79 | 46.12 | 64.31 | 64.12 |

Table C4. Limited Specification Results: Income Groups (Dependent Variable: Poverty Gap) [FE Model]

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Dependent Variable** | **Poverty Gap ($1.90/Day)** | | **Poverty Gap ($3.10/Day)** | |
| **Explanatory Variables** | **UMI** | **LI & LMI** | **UMI** | **LI & LMI** |
| Log of GLP per capita (sum) | -0.2092 | -0.5171 | -0.2941 | -0.5238 |
|  | -2.74\* | -2.45\*\* | -2.36\*\* | -1.98\*\* |
| Log of GDP per capita | -5.4345 | -12.8618 | -9.8691 | -23.7202 |
|  | -6.59\* | -5.80\* | -7.35\* | -8.52\* |
| Domestic Credit | 0.0304 | 0.0662 | 0.0221 | 0.0294 |
|  | 2.43\*\* | 1.72\*\*\* | 1.09 | 0.61 |
| Constant | 52.2659 | 112.7347 | 97.1064 | 211.9249 |
|  | 7.14\* | 6.49\* | 8.15\* | 9.72\* |
|  |  |  |  |  |
| Sigma u | 2.2282 | 7.8214 | 4.5542 | 10.0189 |
| Sigma e | 1.2535 | 3.3610 | 2.0401 | 4.2170 |
| Rho | 0.7596 | 0.8441 | 0.8329 | 0.8495 |
|  |  |  |  |  |
| N-Obs | 208 | 230 | 208 | 230 |
| N-Groups | 21 | 49 | 21 | 49 |
| R2 (Within) | 0.3672 | 0.2806 | 0.4479 | 0.4631 |
| R2 (Between) | 0.1277 | 0.5955 | 0.1262 | 0.7010 |
| R2 (Overall) | 0.2861 | 0.5454 | 0.3409 | 0.6261 |
| F-Statistic/Wald Chi2 (Model) | 35.58 | 23.15 | 49.75 | 51.17 |

Notes: t values below coefficients \*, \*\*, and \*\*\* denote significance at 1%, 5%, and 10%, respectively.

UMI: Upper Middle-Income LMI: Lower Middle-Income LI: Low-Income

## **Time-Period (2002-Onward)**

Table C5. Limited Specification Results: 2002-Onward (Dependent Variable: Poverty HC Ratio)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Dependent Variable** | **Poverty HC Ratio ($1.90/Day)** | | **Poverty HC Ratio ($3.10/Day)** | |
| **Explanatory Variables** | **Fixed Effects** | **Random Effects** | **Fixed Effects** | **Random Effects** |
| Log of GLP per capita (sum) | -0.0620 | -0.1561 | -0.0570 | -0.5115 |
|  | -0.31 | -0.79 | -0.19 | -1.82\*\*\* |
| Log of GDP per capita | -15.8780 | -19.5394 | -28.0467 | -27.4584 |
|  | -7.54\* | -14.33\* | -9.05\* | -16.99\* |
| Domestic Credit | -0.0370 | 0.0024 | -0.1239 | -0.0835 |
|  | -1.07 | 0.08 | -2.43\*\* | -2.06\*\* |
| Constant | 153.6864 | 186.6772 | 276.6847 | 272.4564 |
|  | 8.76\* | 17.14\* | 10.72\* | 21.16\* |
|  |  |  |  |  |
| Sigma u | 14.1047 | 11.2325 | 14.3569 | 11.7123 |
| Sigma e | 4.0961 | 4.0961 | 6.0252 | 6.0252 |
| Rho | 0.9222 | 0.8826 | 0.8503 | 0.7907 |
|  |  |  |  |  |
| N-Obs | 398 | 398 | 398 | 398 |
| N-Groups | 70 | 70 | 70 | 70 |
| Hausman | - | -39.40 | - | 81.120 |
| Theta (Median) | - | 0.8206 | - | 0.7509 |
| R2 (Within) | 0.3229 | 0.3201 | 0.4453 | 0.4403 |
| R2 (Between) | 0.7215 | 0.7245 | 0.7737 | 0.7877 |
| R2 (Overall) | 0.5912 | 0.5986 | 0.6559 | 0.6718 |
| F-Statistic/Wald Chi2 (Model) | 51.66 | 350.78 | 86.95 | 549.06 |

Table C6. Limited Specification Results: 2002-Onward (Dependent Variable: Poverty Gap)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Dependent Variable** | **Poverty Gap ($1.90/Day)** | | **Poverty Gap ($3.10/Day)** | |
| **Explanatory Variables** | **Fixed Effects** | **Random Effects** | **Fixed Effects** | **Random Effects** |
| Log of GLP per capita (sum) | -0.1408 | -0.1507 | -0.1029 | -0.1979 |
|  | -1.32 | -1.43 | -0.70 | -1.38 |
| Log of GDP per capita | -5.6941 | -7.8067 | -12.2904 | -14.3684 |
|  | -5.04\* | -10.26\* | -7.93\* | -14.93\* |
| Domestic Credit | -0.0008 | 0.0174 | -0.0308 | -0.0059 |
|  | -0.04 | 1.07 | -1.21 | -0.27 |
| Constant | 55.0409 | 73.8682 | 119.6296 | 138.3434 |
|  | 5.85\* | 12.14\* | 9.27\* | 18.00\* |
|  |  |  |  |  |
| Sigma u | 7.9454 | 6.5725 | 9.4782 | 7.7417 |
| Sigma e | 2.1968 | 2.1968 | 3.0130 | 3.0130 |
| Rho | 0.9290 | 0.8995 | 0.9082 | 0.8685 |
|  |  |  |  |  |
| N-Obs | 398 | 398 | 398 | 398 |
| N-Groups | 70 | 70 | 70 | 70 |
| Hausman | - | -50.65 | - | -127.11 |
| Theta (Median) | - | 0.8352 | - | 0.8090 |
| R2 (Within) | 0.1734 | 0.1717 | 0.3557 | 0.3533 |
| R2 (Between) | 0.6202 | 0.6135 | 0.7361 | 0.7405 |
| R2 (Overall) | 0.4965 | 0.4933 | 0.6170 | 0.6250 |
| F-Statistic/Wald Chi2 (Model) | 22.73 | 174.41 | 59.81 | 395.78 |

Notes: t/z values below coefficients \*, \*\*, and \*\*\* denote significance at 1%, 5%, and 10%, respectively.

## **Microfinance Indicators**

Table C7. Limited Specification Results: Effect of Female Borrowers on Poverty [FE Model]

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Dependent Variable** | **Poverty HC Ratio** | | **Poverty Gap** | |
| **Explanatory Variables** | **$1.90/Day** | **$3.10/Day** | **$1.90/Day** | **$3.10/Day** |
| Log of GLP per capita (sum) | -0.5302 | -0.5742 | -0.3546 | -0.4352 |
|  | -2.55\*\* | -2.04\*\* | -3.16\* | -2.90\* |
| Percent Female Borrowers | -6.4686 | -9.9491 | -1.2641 | -4.1875 |
|  | -4.21\* | -4.77\* | -1.52 | -3.77\* |
| Log of GDP per capita | -19.8797 | -30.5591 | -8.5331 | -15.2905 |
|  | -8.88\* | -10.06\* | -7.05\* | -9.45\* |
| Domestic Credit | 0.0450 | -0.0388 | 0.0511 | 0.0334 |
|  | 1.28 | -0.81 | 2.69\* | 1.31 |
| Constant | 190.6797 | 302.2397 | 79.5797 | 146.9091 |
|  | 10.30\* | 12.03\* | 7.95\* | 10.97\* |
|  |  |  |  |  |
| Sigma u | 13.2925 | 14.5625 | 7.3139 | 9.0637 |
| Sigma e | 4.6971 | 6.3723 | 2.5394 | 3.3963 |
| Rho | 0.8890 | 0.8393 | 0.8924 | 0.8769 |
|  |  |  |  |  |
| N-Obs | 437 | 437 | 437 | 437 |
| N-Groups | 70 | 70 | 70 | 70 |
| R2 (Within) | 0.3872 | 0.4850 | 0.2539 | 0.4135 |
| R2 (Between) | 0.7239 | 0.7715 | 0.6144 | 0.7367 |
| R2 (Overall) | 0.6095 | 0.6621 | 0.5044 | 0.6309 |
| F-Statistic (Model) | 57.34 | 85.45 | 30.88 | 63.99 |

Table C8. Limited Specification Results: Effect of MFI Count on Poverty [FE Model]

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Dependent Variable** | **Poverty HC Ratio** | | **Poverty Gap** | |
| **Explanatory Variables** | **$1.90/Day** | **$3.10/Day** | **$1.90/Day** | **$3.10/Day** |
| MFI Count | -0.0616 | -0.0600 | -0.0313 | -0.0443 |
|  | -2.55\*\* | -1.83\*\*\* | -2.40\*\* | -2.54\*\* |
| Log of GDP per capita | -22.1527 | -33.9901 | -9.6178 | -17.0711 |
|  | -10.46\* | -11.85\* | -8.44\* | -11.17\* |
| Domestic Credit | 0.0502 | -0.0266 | 0.0510 | 0.0366 |
|  | 1.41 | -0.55 | 2.66\* | 1.42 |
| Constant | 207.1242 | 326.8508 | 88.0928 | 160.0898 |
|  | 11.77\* | 13.72\* | 9.30\* | 12.61\* |
|  |  |  |  |  |
| Sigma u | 13.1529 | 15.5582 | 7.3174 | 9.2246 |
| Sigma e | 4.8203 | 6.5264 | 2.5927 | 3.4772 |
| Rho | 0.8816 | 0.8504 | 0.8885 | 0.8756 |
|  |  |  |  |  |
| N-Obs | 443 | 443 | 443 | 443 |
| N-Groups | 70 | 70 | 70 | 70 |
| R2 (Within) | 0.3719 | 0.4684 | 0.2495 | 0.4020 |
| R2 (Between) | 0.7137 | 0.7672 | 0.5964 | 0.7228 |
| R2 (Overall) | 0.5890 | 0.6510 | 0.4743 | 0.6071 |
| F-Statistic (Model) | 73.01 | 108.66 | 41.00 | 82.92 |

Notes: t values below coefficients \*, \*\*, and \*\*\* denote significance at 1%, 5%, and 10%, respectively.

## **Sensitivity Analysis with World Development Indicator (WDI) Control Variables**

Table C9. Sensitivity Analysis Results: WDI Control Variables [FE Model]

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Dependent Variable** | **Poverty HC Ratio** | | **Poverty Gap** | |
| **Explanatory Variables** | **$1.90/Day** | **$3.10/Day** | **$1.90/Day** | **$3.10/Day** |
| Log of GLP per capita (sum) | -0.6218 | -0.6304 | -0.4176 | -0.5030 |
|  | -2.38\*\* | -1.87\*\*\* | -2.89\* | -2.64\* |
| Log of GDP per capita | -16.4758 | -21.9121 | -8.8588 | -12.7409 |
|  | -4.91\* | -5.06\* | -4.77\* | -5.21\* |
| Domestic Credit | 0.0251 | -0.0153 | 0.0328 | 0.0233 |
|  | 0.66 | -0.31 | 1.55 | 0.84 |
| Pop. Density | -0.1036 | -0.0753 | -0.0119 | -0.0476 |
|  | -3.16\* | -1.78\*\*\* | -0.66 | -2.00\*\* |
| Pop. Growth | 5.6786 | 8.1262 | 1.3358 | 3.6707 |
|  | 3.04\* | 3.37\* | 1.29 | 2.70\* |
| Rural Pop. Growth | -3.7125 | -4.8648 | -1.1202 | -2.4463 |
|  | -2.52\*\* | -2.56\*\* | -1.37 | -2.28\*\* |
| Age Dependency Ratio | 0.5728 | 1.2928 | -0.0033 | 0.4037 |
|  | 4.80\* | 8.38\* | -0.05 | 4.64\* |
| Fertility Rate | -5.5907 | -15.2075 | 2.1207 | -3.3191 |
|  | -3.11\* | -6.55\* | 2.13\*\* | -2.54\*\* |
| Labor Force Participation Rate | -0.5222 | -0.0578 | -0.2098 | -0.2644 |
|  | -1.60 | -0.14 | -1.16 | -1.11 |
| Employment-Pop. Ratio | 0.5650 | 0.3905 | 0.1513 | 0.2970 |
|  | 1.97\*\* | 1.06 | 0.95 | 1.42 |
| Agric. Land (% of Total Land) | -0.3803 | -0.4962 | -0.0512 | -0.2249 |
|  | -2.32\*\* | -2.34\*\* | -0.56 | -1.88\*\*\* |
| Agric. Value Added/Worker | 0.0004 | 0.0002 | 0.0003 | 0.0003 |
|  | 1.27 | 0.37 | 1.50 | 1.21 |
| Constant | 161.2033 | 189.0813 | 82.5902 | 118.2106 |
|  | 5.13\* | 4.66\* | 4.76\* | 5.17\* |
|  |  |  |  |  |
| Sigma u | 22.1993 | 22.8963 | 6.7452 | 12.0375 |
| Sigma e | 4.4633 | 5.7626 | 2.4687 | 3.2489 |
| Rho | 0.9611 | 0.9404 | 0.8819 | 0.9321 |
|  |  |  |  |  |
| N-Obs | 388 | 388 | 388 | 388 |
| N-Groups | 67 | 67 | 67 | 67 |
| R2 (Within) | 0.4796 | 0.5913 | 0.3225 | 0.4884 |
| R2 (Between) | 0.3776 | 0.5072 | 0.6698 | 0.5727 |
| R2 (Overall) | 0.3616 | 0.4451 | 0.6125 | 0.5391 |
| F-Statistic (Model) | 23.73 | 37.25 | 12.26 | 24.58 |

Notes: t values below coefficients \*, \*\*, and \*\*\* denote significance at 1%, 5%, and 10%, respectively.

1. “Microfinance” and “microcredit” are two distinct terms which signal for some a significant difference in opinion. “Microcredit” refers specifically to small loans, while “microfinance” is a broader term that embraces efforts to provide a range of services to low-income people, such as savings, insurance, and in some places even assistance in distributing and marketing clients’ output. “Microcredit” was initially coined to refer to institutions (largely NGOs) focused on getting loans to the very poor, with the explicit goals of poverty reduction and social change. The move to the term “microfinance” came with the recognition that poor households could benefit from access to financial services generally, and not just credit for microenterprises (Beatriz and Morduch, 2010, p. 15-16). See Beatriz and Morduch (2010), “The Economics of Microﬁnance” for a discussion of the distinction between “microcredit” and “microfinance” and the evolution of the terms. [↑](#footnote-ref-1)
2. 571.5 million people including borrowers’ households. Figure reported by the Microcredit Summit Campaign and is based on an assumption of an average family size of 5. These figures only consider current *borrowers with loans*, not people receiving other financial services such as savings plans/accounts. [↑](#footnote-ref-2)
3. Precisely 18.8 percent (CAGR calculation—1997: 13,478,797 clients; 2013: 211,119,547 clients). [↑](#footnote-ref-3)
4. Buera, et al. (2014) points out that the dramatic growth in the number of institutions is certainly overstated due to an increase in survey participation, but says that despite this, the growth is “real and dramatic”. They cite the example of a single program, the National Bank for Agriculture and Rural Development (NABARD) in India, which expanded its number of clients from 146,000 to 49 million from 1997 to 2010 (p.7). [↑](#footnote-ref-4)
5. It should be noted however, that those other institutions may have many of the same characteristics of MFIs and the distinction may not always usable, particularly when categorizing institutions for regulatory purposes. (Hardy, et al. 2002. p. 4). [↑](#footnote-ref-5)
6. Note: Imai, et al. (2012) is the 3rd iteration of previous/similar work that the authors completed in 2010. [↑](#footnote-ref-6)
7. The instruments that Imai et al. use for IV estimation are the cost of enforcing contracts at the country level and a 5-year lag of average of gross loan portfolio weighted by the number of MFIs for each country (p. 1677). [↑](#footnote-ref-7)
8. The instruments that Miled and Rejeb use are the cost of enforcing contracts at the country level and a 6-year lag of average of gross loan portfolio weighted by the number of MFIs for each country (p. 707). [↑](#footnote-ref-8)
9. The instruments that Donou-Adonsou and Sylwester use are measures of ethnic tensions and rule of law at the country level (p. 86). [↑](#footnote-ref-9)
10. Note: While GLP as reported by MIX is the variable that has been used in other literature, it is unclear if GLP is measured using purchasing power parity or whether it controls for inflation. [↑](#footnote-ref-10)
11. Imai, et al. directs the reader to Ahlin et al., 2011 for details regarding determination of the level of validity in these sub-samples. [↑](#footnote-ref-11)
12. The specific variables from the World Bank WDI that they compare are: (a) branches, microfinance institutions (per 100,000 adults); (b) deposit accounts, microfinance institutions (per 1000 adults); and (c) loan accounts, microfinance institutions (per 1000 adults). [↑](#footnote-ref-12)
13. In preliminary/early regressions, countries of all income levels were included in regressions. After consideration, observations for countries that were considered “high-income” countries by the World Bank’s income classifications were dropped because microfinance generally targets lower income, developing countries. Even though high-income countries represented a small portion of the sample in the original limited specification, excluding them appears to have had a modest effect on the strength of the model. The magnitude and significance of the impact of GLP per capita on poverty increased, and both the adjusted-R2 and R2-within increased very slightly. [↑](#footnote-ref-13)
14. The model does not include a measure of educational attainment or government spending on education, which would be appropriate to include because education (both theoretically and empirically) has a significant impact on income and poverty. This analysis did consider including a variable describing government spending on education as a % of GDP, however including this variable reduced the sample size considerably (from 388 to 246). When this variable is added the coefficient of log of GLP per capita is still negative, but is not statistically significant. It is possible that this result is due not to the inclusion of the new control variable, but to the smaller sample size. [↑](#footnote-ref-14)