Impact of Microfinance on Poverty and Microenterprises: A Meta-analysis

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Abstract

We conduct a meta-analysis to review 25 empirical studies with a total of 595 estimates of the impact of microfinance on poverty reduction and microenterprise performance. We consider four proxies for poverty and three for microenterprise performance in order to examine the empirical evidence, and to provide a general conclusion on the impacts of microfinance, while addressing issues of within and between-study variations. The proxies for poverty include consumption/expenditure, assets, income and income growth while those for microenterprise performance include labour supply, business profits and revenue. Overall, we find no robust evidence of any significant impact on the performance of microenterprises. With regards to impact on poverty, there is no evidence of any strong positive, impact especially on consumption/expenditure, as the evidence mainly suggests an insignificant impact. However, we find a significant impact of microcredit on assets, which is positive but weak and thus is of no practical economic relevance. Evidence also indicates a negative impact on income growth.

1. Introduction

The microfinance industry, which includes services such as microcredit, micro-insurance, micro-savings and money transfers, amongst other things, has caught the attention of a wide range of people. Microfinance over the past few decades has grown to become one of the major development programmes in the world, both in terms of the number of people targeted as well as the financial input that it receives (van Rooyen et al., 2012). The industry has attained considerable growth around the world with the promise of helping alleviate poverty. While the truth behind its ability to alleviate poverty, amongst other things, is still a subject of public discourse, Copestake (2002) indicates that a major reason for the popularity and growth of the industry is its 'market friendly' nature which is characterised by flexible lending mechanisms. Some, however, remain sceptical about the positive impact of microfinance and thus donors (both prospective and current), government agencies, policy makers and stakeholders are showing much interest in understanding what works, and what does not work, in microfinance.

The most basic underlying theories of the impact of microfinance assume that a microfinance client is a sole operator of an income generating activity, with an output that is constrained by either a high marginal credit cost, relative to marginal returns or by lack of capital. Thus, access to 'cheap' capital, which eases the constraints, allows for the increase of output, profits, net income and subsequently, the welfare of the borrower (de Mel et al., 2008, Duvendack et al., 2011). Another aspect of microfinance impact theory focuses on the psychology of borrowers. Here, the assumption is that credit has the potential to affect the 'mental models' that influence the business decisions of a borrower (Nino-Zarazua and Copestake, 2008). Related to this, based on the assumption that borrowers would not borrow if credit did make them worse off (Rosenberg, 2010), research in the area of borrower psychology suggests that it is unlikely for credit to have an adverse effect on the borrower. Consequently, one strand of the evidence suggests that indeed microfinance is effective and is benefiting clients (see, e.g., Sebstad and Chen, 1996; Morduch, 1999; Khandker, 2005; Imai et al., 2010; Imai and Azam, 2012).

On the contrary, the possibility that microfinance could have a negative impact has also been discussed. For instance, it has been argued that credit can be associated with various indicators of the poor's individual and household socio-economic status, and depending on which indicator, effects could be either positive or negative (Kabeer, 2005). Wydick (1999), for example, suggests that families that have access to credit and build up productive microenterprises may employ the labour of their children, instead of hired labour. As a result, in the long-run, while this may increase the income level of the household, it affects the child's schooling adversely. The negative effects of microfinance is, thus, also supported by a wide range of evidence (see, e.g., Hulme and Mosley, 1996; Hulme, 2000; Copestake, 2002; Hoque, 2005; Shaw, 2004; Nghiem et al., 2012).

Therefore, as it stands, the evidence about the impact of microfinance interventions across the world remain very controversial and this is acting as a catalyst for development economists to conduct thorough empirical studies to ascertain the impact of microfinance. There is a need for more evidence to ascertain what the impacts of microfinance interventions entail, and this points to the urgent need to pull together, and analyse, the existing evidence on the impact of microfinance interventions. To this end, recent systematic reviews such as Duvendack et al. (2011), Stewart et al. (2010) and van Rooyen et al. (2012) conduct non-empirical synthesis of the existing literature on the impact of microfinance, and inferences drawn from these studies mainly suggest that there is no visible impact of microfinance. For instance, Stewart et al. (2010) indicate that, overall, microcredit positively influences the level of engagement of the poor in economic activities. However, there is evidence of lower income associated with microfinance clients who have been borrowers for relatively longer periods. Furthermore, this synthesis also reveals that microcredit has no significant impact on non-financial asset accumulation.

Given the findings from these systematic reviews, it is worthwhile to examine if an empirical synthesis would lead to any new conclusions. Thus, we conduct a meta-analysis of the empirical evidence on the impact of microfinance interventions on poverty and microenterprises. We focus on two measures of microfinance used in the literature - microcredit and access to microcredit, four proxies for poverty - consumption/expenditure, assets, income and income growth, and three proxies for microenterprises - labour supply, business profits and revenue. Here, studies that use microcredit as a measure of microfinance are those that consider amount borrowed or loan size as an independent variable, and thus examine the impact of loan received on outcome measures. On the contrary, those that consider access to microcredit examine whether (or not) membership in a microcredit programme or the receipt of a loan impacts our outcome measures. We formulate four major hypotheses to guide us in this research: 1) Microcredit has a positive impact on poverty reduction (H1), 2) Microcredit has a positive impact on the performance of microenterprises (H2); 3) Access to microcredit has a positive impact on poverty reduction (H3); 4) Access to microcredit has a positive impact on the performance of microenterprises (H4). For each hypothesis, we focus on sub-hypotheses, which relate to the mentioned poverty and microenterprise measures.

Furthermore, the heterogeneity in reported findings on the impact of microfinance interventions have often been associated with various study specific characteristics (Duvendack et al., 2011). In theory, a number of circumstances are associated with microfinance and these have been argued to affect how microfinance affects economic and social outcomes. For instance, the use of different measures of poverty, female versus male borrowers, effects on the poorest versus not so poor, the level of analysis (household level versus individual level), the lending type (group versus individual), the purpose of the loan, and different effects in different countries. Thus, in our meta-regression, we examine if the impact of microfinance on our outcome variables are affected by these variations.

Specifically, this paper makes the following contributions; first, we address the issue of heterogeneity and provide a general conclusion on the empirical evidence on the impact of microfinance interventions poverty and microenterprises. This is relevant given that in the presence of heterogeneity, it is difficult to draw a valid conclusion. Second, with the results from our meta-analysis, we lay a foundation for, and guide future studies in, examining areas of particular importance. For instance, we identify the need to conduct further theoretical research that would guide hypothesis formulation and promote the robustness of empirical studies that examine the impact of microfinance. We also identify the need to conduct more primary studies on the impact of microfinance interventions using various metrics for microfinance other than microcredit, and perhaps adopt a standard for measuring outcomes. Third, we provide evidence of the genuine effects of microfinance beyond publication bias. In the presence of publication bias and given the disparity in the existing literature regarding the effects of microfinance, policy formulation is impeded.

Publication selection bias occurs when researchers, editors and reviewers are predisposed to selecting studies with specific results (for example statistically significant results consistent with the predictions of theory). This has been considered a threat to empirical economics (Stanley, 2008). In fact, without some correction for publication bias, a literature that appears to present a large and significant empirical effect could actually be misleading. With regards to microfinance, this bias can actually extend to the predisposition to reject studies that report negatively on the impacts of microfinance interventions. However, we find no robust evidence of publication bias in the literature.

Overall, our study is an important step to dealing with the extant deadlock regarding the impacts of microfinance (whether positive, negative or non-existent), and also provide some explanations to how variations in the existing literature affect the nature of reported effects of microfinance.

2. Brief Overview of Concepts and Evidence

Measuring the impact of microfinance interventions has been identified to be a very challenging task (Berhane and Gardebroek, 2011) because of various problems including problems of accounting for potential biases[1] (Pitt and Khandker, 1998) which may arise from self-selection and program placement (Tedeschi, 2008), amongst other things. As a result, various approaches have emerged over the years and have been used in microfinance impact assessments. There is an extensive discussion[2] on the validity of some of these approaches, with some criticisms questioning the validity of some results presented in the literature (see, e.g., Roodman and Morduch (2013)). Notably, one strand of the existing literature which examines the impact of microfinance make use of quasi-experimental techniques and also cross-sectional data while employing instruments to deal with potential selection problems (Pitt and Khandker, 1998), while some adopt a randomized experimental approach (see, e.g., Karlan and Zinman (2007), Banerjee et al. (2009), Karlan et al. (2009) and Feigenberg et al. (2010), amongst others).

Overall, the common trend in the existing literature that examines the impact of microfinance on poverty is to adopt a framework that considers microcredit as an exogenous ‘treatment’ on households or individual borrowers to one, or more, indicators of poverty. A number of

[1] See Tedeschi (2008) for a review of some potential biases faced by microfinance impact assessment researchers.
[2] For detailed discussion on impact assessment methods used in the literature as well as arguments concerning results validity, see, Morduch (1999), Roodman and Morduch (2013), Duvendack et al. (2011) and Berhane and Gardebroek (2011).

studies have emerged and despite the slight differences in case studies and methodologies used, the literature on the impact of microfinance on poverty is highly debatable and point to several specific conclusions. Some of the proxies used in the literature to measure poverty include income levels, assets and consumption/expenditure, as well as a few studies that have developed indices for poverty.

Generally, microloans are targeted towards the poor (that is those below the poverty line), however, a number of individuals slightly above the poverty line (non-poor borrowers) also benefit from microloans as well. It is expected that borrowers above the poverty line would benefit more from microloans (Hulme and Mosley, 1996). Usually, microfinance is expected to have a long-run positive impact only if borrowers have viable investments and are equipped with the necessary skills to sustain a business. In most cases, non-poor borrowers do have such investment opportunities and the required skills. Thus, when MFIs serve such clients, the impacts of interventions are usually positive, especially on income and consumption levels. Li et al. (2011), using a two year panel dataset from rural China, provides evidence to support this. Furthermore, Wood and Sharif (1997) argue that because poorer borrowers face major constraints in investing their loans into highly productive activities, they tend to benefit less from microcredit. Nonetheless, evidence (see, e.g., Banerjee et al. (2009)) suggests that with the necessary support and training to the very poor borrowers, the effects of microfinance can be positive. As a result, it is generally believed that with a viable investment and appropriate training, borrowers (whether poor or non-poor) would experience increases in business productivity. However, microcredit alone, and in itself, is limited in effecting change in the lives of borrowers (see Karnani (2007), Banerjee et al. (2009) and Daley-Harris (2009)).

Using assets and consumption/expenditure as a proxy for poverty can be misleading if the dataset used in the analysis does not cover a sufficiently long period. The underlying logic is that after MFIs provide microloans, borrowers can spread-out these loans over a short period of time for consumption or for the purchase of new items. Thus, in the short-run, there is an increase in the consumption/expenditure level of borrowers but, in the long-run, there is a significant decline. On the other hand, some borrowers put their loans into productive use and as their income levels increase, there is a corresponding increase in assets, consumption and expenditure as well. Nonetheless, whether microloans are used for productive purposes or not, it is expected that the effects will be positive on assets, consumption and expenditure, at least in the short-run. Studies such as Pitt and Khandker (1998), Khandker (2005), Hoque (2004), Berhane and Gardebroek (2011), Li et al. (2011), Nghiem et al. (2012), Kaboski and Townsend (2012) and Imai and Azam (2012) examine the impact of microfinance on at least one of these proxies. Pitt and Khandker (1998) found that microcredit has a very significant positive impact on consumption, but mainly for female borrowers. Subsequent studies such as Khandker (2005), Berhane and Gardebroek (2011) and Imai and Azam (2012) present evidence supporting the positive effect of microfinance on consumption. On the other hand, evidence presented by Morduch (1998), Hoque (2004) and Nghiem et al. (2012) indicate that the effects of microfinance on consumption is insignificant. These studies conclude that the insignificant effect is either due to the small value of microloans issued or failure to use microloans for productive purposes. Kaboski and Townsend (2012) present evidence of positive effects on consumption and income growth in the short-run but negative effects on assets.

Some studies use poverty indices to measure poverty. These indices usually capture various dimensions of poverty including those discussed earlier. Studies such as Imai et al. (2010) and Imai et al. (2012) examine the effects of microfinance on poverty using poverty indices. In both cases, evidence supports the poverty reducing effect of microfinance.

As discussed earlier, the general consensus is that microloans that are put into productive use impact positively on the productivity of microenterprises, especially when borrowers have the necessary skills to sustain their businesses. Copestake et al. (2001) and Tedeschi (2008) provide evidence to support the positive effects of microfinance on microenterprise profits. Copestake et al. (2001) further argue that it is better for clients to remain in microcredit programmes, rather than leave after their first loans. This is because clients who graduate from their first loans to subsequent loans, on average, have higher returns as evidenced in the significant profit growth in their businesses as well as increased household income. It was also found that about 50 per cent of clients left microfinance programmes after receiving their first loans and this category of borrowers were worse off after leaving with their first loans. However, Copestake et al. (2005a) considered a sample from Peru and found a negative impact of microfinance on profits of microenterprises. This negative finding was attributed to the rigid nature of loan repayment schedules which, in most cases, does not give borrowers the opportunity to start receiving returns on their investment before repayments are due. This is usually the case for borrowers who invest in agriculture.

In summary, evidence from existing studies on the impact of microfinance interventions on poverty and microenterprises remain mixed[3].

3. Methodology & Data

3.1. Data Collection: Identifying Relevant Studies

The data used in this study is empirical results retrieved from existing studies that have been included in our study. In order to identify relevant literature for this study, we first searched five electronic databases – JSTOR, Business Source Complete, EconLit, Google Scholar and ProQuest (itself containing over 30 databases), using various keywords for microfinance, poverty and microenterprises[4]. Next we conduct a manual search process, and also examine recent systematic reviews in the area (Stewart et al., 2010, Duvendack et al., 2011, Vaessen et al., 2012, van Rooyen et al., 2012) to ensure all relevant empirical studies have been included.

[3] See Banerjee (2003) for a detailed review of the literature on the impact of microfinance.

[4] Keywords for microfinance include microfinance, micro-finance, microcredit, micro-credit, micro-lease, microloan, micro-Savings, micro-insurance, micro-banking, micro-bank, credit, MFI and small loan(s). Keywords for poverty and microenterprise include poverty, income, consumption, expenditure, assets, microenterprise, micro-enterprise, micro-business, small business and micro-franchise.

Given the hypotheses we aim to test, we include only studies that use either microcredit or access to credit as the measure of microfinance, and examine impacts on consumption/expenditure, assets, income, income growth, labour supply, business profits and revenue. Thus, for a study to be included in this meta-analysis, it had to be an empirical study that examines at least one of the above mentioned variables as outcome variables and uses microcredit and/or access to credit as the independent variable. Consequently, we exclude studies that examine impacts on poverty indices (e.g., Imai et al., 2010), and those that consider micro-savings as a measure of microfinance (e.g., Ashraf et al., 2010; Dupas and Robinson, 2013). In addition, given that partial correlation coefficients are calculated to allow for comparability of studies, studies that meet the above criteria but report only coefficients and not all relevant statistics to enable the correlation coefficient calculation are excluded.

Overall, we include 25 studies, with a total of 595 meta-observations in our meta-analysis. Tables 1A and 1B present an overview of studies included in this meta-analysis.

3.2. Empirical Design

3.2.1. The Concept of Meta-analysis

Meta-analysis involves the statistical analysis of previously conducted studies or reported research findings on a given empirical effect, intervention, hypothesis or research question. It allows the combination of all relevant literature in a particular research area using statistical methods with the aim of evaluating and synthesizing the existing evidence (Card and Krueger, 1995). Meta-analysis makes it possible to combine, and contrast, different studies, with the view to identifying patterns in existing findings and other relevant relationships which can only be observed in the context of multiple studies. By statistically combining the empirical results from existing studies, the 'power' of the analysis is increased; hence, the precision of estimates are improved.

In meta-analysis, an effect size, which is a weighted mean, is usually derived from the estimates or effect sizes reported in the involved individual studies. Thus meta-analysis combines the less precise effect sizes reported in individual studies and derives a more precise estimate of the genuine effect size between variables.

The use of this methodology has been prominent in the areas of medicine, education and social research policy, but over the past few years, a growing number of researchers in economics have adopted the tool in the hope of enhancing the quality and precision of evidence synthesis in economics (see, e.g., Card and Krueger, 1995; Stanley and Doucouliagos, 2007; Stanley, 2008; De Dominicis et al., 2008; Ugur, 2013). This is indeed relevant given that there is an exponential expansion in the volume of existing literature across the various research areas in economics. In addition, with the high level of heterogeneity which accompanies the findings from these studies, meta-analysis is effective in accounting for the various sources of bias and heterogeneity.

A major problem however with the use of meta-analysis, is the issue of publication bias. In the presence of publication bias, it can be argued that studies involved in meta-analysis may not be truly representative of all relevant studies in an area of interest. Nonetheless, like any other statistical tools, various techniques have emerged to deal with the problem of publication bias, some of which have been adopted for use in this study.

3.2.2. Empirical Model Specifications

This study conducts a meta-analysis of the data collected and this is done in three stages. The first stage involves the calculation of the fixed effects estimates (FEEs) for the weighted mean of the various estimates that have been reported for each study. Stanley et al. (2009) propose that FEEs are efficient given that the estimates which have been reported by the original studies are derived from the same population and have a common mean. In addition, FEES are more reliable than simple means, and compared to random-effects weighted means, they are less affected by publication bias (Henmi and Copas, 2010, Stanley, 2008, Stanley and Doucouliagos, 2014).

Second, to test if reported FEEs are affected by publication selection bias, we conduct precision effect tests (PETs) and funnel asymmetry tests (FATs). The PET/FAT makes it possible to test if a particular microfinance measure has 'genuine effects' on the various outcome measures after controlling for biases like publication selection bias. In the last stage of the meta-analysis, we examine if variations in reported estimates can be attributed to study characteristics such as publication year and type, econometric methodology, data type and borrower differences. Thus, a meta-regression is conducted in order to test for genuine effects on the outcome variables after controlling for various biases and the effects of moderating variables (variations) such as those mentioned earlier. This process is conducted using partial correlation coefficients (PCCs) derived from estimates extracted from the chosen studies.

PCCs are used because they measure the association between microfinance and the outcome variables while other independent variables are held constant. Basically, they are comparable across different studies as they are independent of the metrics used in measuring both the dependent and explanatory variables, and they are also widely used in meta-analysis (see for example Doucouliagos and Ulubasoglu, 2008; Alptekin and Levine, 2012; Ugur, 2013).

The PCC for each effect estimate is calculated as follows;

$$r_i = \frac{t_i}{\sqrt{t_i^2 + df_i}} \tag{1}$$

Similarly, the standard error of the above coefficient is calculated as

$$SE_{ri} = \sqrt{\frac{1 - r_i^2}{df_i}} \tag{2}$$

Where r_i and SE_{ri} represent the PCC and the standard error of the PCC respectively. The standard error represents the variance which is attributed to sampling error and it is used in the calculation of the FEEs for the study based weighted means. t_i, represents the t-statistic which is associated with the given effect-size estimate and df_i is the degrees of freedom that corresponds with the estimates as reported in the studies.

For the weighted means used in this study, the approach used by Stanley and Doucouliagos (2007), Stanley (2008) and De Dominicis et al. (2008) was adopted. They report that weighted means can be calculated using the relation;

$$\bar{X} = \frac{\sum w_i r_i}{\sum w_i} \tag{3}$$

Where $\bar{X}$ is the weighted mean of the reported estimates, r_i, is the partial correlation coefficient as calculated in equation 1 above and w_i, is the weight which varies depending on whether $\bar{X}$ is a random effect mean or fixed effect mean.

For fixed effect estimates (FEEs), the weight, w_i is given as the inverse of the square of the standard error associated with the PCCs as derived in equation 2 above. Thus, equation 3 can be re-expressed as equation 4 as the fixed effect estimates for the weighted mean of the partial correlations.

$$\bar{X}_{FEE} = \frac{\sum r_i \left(\frac{1}{SE_{ri}^2}\right)}{\sum \frac{1}{SE_{ri}^2}} \tag{4}$$

Where $\bar{X}_{FEE}$ is the fixed effect estimate weighted mean, and r_i and SE_{ri} remain as they are above. The fixed effect estimate weights account for the within-study variations by distributing weights, such that estimates that are less precise are assigned lower weights, while higher weights are assigned to more precise estimates. Thus, the fixed effects weighted means are more reliable compared to the simple means. Nonetheless, if the estimates from the original study are subject to within study dependence bias as a result of data overlap and/or publication selection bias, the FEE weighted means cannot be considered as a consistent measure of partial correlations or 'genuine effect size'. The idea here is that FEEs work with the assumption that effects size estimated from each individual study are a fixed effect which are subject to the possibility of sampling error captured by the standard error associated with the estimate (De Dominicis et al., 2008). It is important to note, however, that this assumption is invalid when the estimation methods and model specifications used by each study differs. On a study-by-study basis, the use of the FEEs, which can also be referred to as the study-specific weighted means, provide relevant information for understanding the differences and similarities between the findings that have been reported by the original studies. This is a common practice in the existing literature in the healthcare, education and social care arena that have reported meta-analyses mainly for randomised control trials. In such studies, the fixed effect estimates are reliable estimates of effect size, given that between-study heterogeneity is minimized by the use of appropriate study designs which include a random selection of control and intervention groups.

We attempt to deal with the risk of bias and data dependence by conducting the precision effect tests (PETs), funnel asymmetry tests (FATs) and also precision effect tests with standard errors (PEESE). Conducting these tests makes it possible to ascertain whether the PCCs which have been derived from the reported estimates in the original studies are subject to publication selection bias and also whether or not they represent a true measure of genuine effects beyond bias. The PET/FAT analysis involves the estimation of a bivariate weighted least square (WLS) model. Egger et al. (1997) propose the following model to test for publication selection bias;

$$r_i = \beta_0 + \alpha_0(SE_{ri}) + u_i \tag{5}$$

Where r_i is the effect estimate, β_0, α_0 represent the constant term and the slope coefficient respectively while SE_{ri} is the standard error of the estimate. Egger et al. (1997) suggest that publication bias is present if the slope coefficient is significantly different to zero. Furthermore, the model also suggests that in the absence of bias (that is the slope coefficient is not significantly different to zero), the effect estimate would randomly vary around the true effect, which is the intercept term. Nonetheless, equation 5 above would not be efficient in determining whether the effect estimates are genuine since it is heteroskedastic in nature (Hawkes and Ugur, 2012, Stanley, 2008) and due to the fact that the variance of the reported effect estimates are not constant. In this regard, Stanley (2008) recommend that equation 5 be converted into a weighted least square (WLS) model by dividing through it by SE_{ri} to yield equation 6 below. Stanley (2008) demonstrates that this WLS model can be used to test for both publication selection bias (which is the FAT) and for genuine effect beyond selection bias.

$$\frac{r_i}{SE_{ri}} = t_i = \alpha_0 + \beta_0\left(\frac{1}{SE_{ri}}\right) + \varepsilon_i \tag{6}$$

Here, the t-value becomes the dependent variable and the coefficient of the precision $(1/SE_{ri})$ becomes the measure of genuine effect[5]. The funnel asymmetry test involves testing for the following null and alternate hypotheses (equation 7) and if the null hypothesis is rejected, this means that asymmetry exists.

$$\begin{aligned} H_0&: \alpha_0 = 0 \\ H_1&: \alpha_0 \neq 0 \end{aligned} \tag{7}$$

The precision effect test, also known as the test for genuine effect, involves testing of the following null and alternate hypotheses;

$$\begin{aligned} H_0&: \beta_0 = 0 \\ H_1&: \beta_0 \neq 0 \end{aligned} \tag{8}$$

[5] Note that the constant term and the intercept coefficient have now interchanged positions while the error term is newly defined as ε_i.

Stanley (2010) indicates that the reported estimates, and their associated standard errors, have a nonlinear relationship given that the FAT/PET results point to the co-existence of the presence of both publication selection bias and genuine effect. In situations like this, they propose that a precision effect test with standard errors (PEESE) be conducted to account for any nonlinear relationships that may exist. They propose the following PEESE model;

$$r_i = \beta_0 + \alpha_0(SE_{ri}^2) + u_i \tag{9}$$

Dividing this PEESE model by SE_{ri} which suppresses the constant term, with the aim of addressing any potential heteroskedasticity problems, we obtain the following;

$$\frac{r_i}{SE_{ri}} = \beta_0\left(\frac{1}{SE_{ri}}\right) + \alpha_0(SE_{ri}) + u_i\left(\frac{1}{SE_{ri}}\right) \tag{10}$$

Given that

$$\frac{r_i}{SE_{ri}} = t_i$$

and

$$u_i\left(\frac{1}{SE_{ri}}\right) = v_i$$

we get

$$t_i = \beta_0\left(\frac{1}{SE_{ri}}\right) + \alpha_0(SE_{ri}) + v_i \tag{11}$$

Equation 11 tests whether $\beta_0 = 0$ and helps determine if genuine effects are present. The genuine effect in this case, takes into account any nonlinear relationship that may exist with the standard error.

The use of the PET/FAT and PEESE analysis makes it possible to make precise inferences regarding the existence of genuine effects. However, these tests work with the assumption that any moderating variable which may potentially be related to specific study characteristics, or sample differences, are equal to their sample means and are independent of the standard error. As a result, the PET/FAT and PEESE do not include moderating variables. Based on this understanding, this study also conducts a multivariate meta-regression (MRA), which takes into account various moderating variables and allows us to examine the role of such variables on estimated effect-sizes. The MRA specification (12) is usually used to model heterogeneity.

$$t_i = \alpha_0 + \beta_0\left(\frac{1}{SE_{ri}}\right) + \sum \beta_k\left(\frac{Z_{ki}}{SE_{ri}}\right) + \epsilon_i + u_i \tag{12}$$

Where t_i is the t-value associated with each reported estimate, Z_{ki}, is a vector of binary variables that account for variations in the studies, and β_k are the coefficients to be estimated, which explain the effect of each moderating variable on the estimate effect size.

Equation (12) is often estimated by OLS, which is a consistent estimator if the estimated effect sizes retrieved from primary studies are independent from one to another. However, given that primary studies, often, provide more than one estimate, this potentially brings into question the independency among estimates (De Dominicis et al., 2008). Thus, we estimate equation (13) using a multi-level model (hierarchical model) to account for any issues of data dependency. Hence, we estimate the follow model;

$$t_{ji} = \alpha_0 + \beta_0 \left(\frac{1}{SE_{jri}}\right) + \sum \beta_k \frac{(Z_{ki})}{SE_{jri}} + \epsilon_j + u_{ji} \tag{13}$$

Here, t_{ji} is the ith t-value associated with th jth study and k represents the number of moderating variables. Z_{ki} remains as explained, and ϵ_j is the study-specific error term. Both error terms ϵ_j and u_{ji} are normally distributed around the PCCs' mean values such that $\epsilon_i \sim N(0, SE_{ri}^2)$, where SE_{ri}^2 is the square of the standard errors associated with each of the derived PCC, and $u_i \sim N(0, \tau^2)$, where τ^2 is the estimated between-study variance.

4. Findings

4.1. Fixed Effect Estimates (FEEs)

4.1.1. Impact of Microcredit

Table 1A presents fixed effect weighted averages for the impacts of microcredit. From table 1a, we find that four studies with a total of 43 estimates report on the impact of microcredit on assets. The FEEs for impact on assets are positive and significant[6], except for one study (Takahashi et al., 2010), with six estimates that reports a negative and significant average. Based on all 43 estimates, the overall estimated weighted average is 0.0429. Drawing on inferences made by Cohen (1988)[7], we can conclude that although the effect of microcredit on assets is positive, the effect-size represents no meaningful economic significance.

With regards to association between microcredit and income, 60 estimates drawn from nine primary studies are reported. Of the 60 reported estimates, we find that about 81.67% (49 estimates) are statistically insignificant, while the remaining estimates present a positive and statistically significant weighted average. Thus, overall, based on reported FEEs, we can conclude that there is no significant association between microcredit and income. The overall estimated weighted average for all 60 estimates is 0.0105, which is also practically insignificant. For effects on income growth, nine estimates drawn from three primary studies

[6] Statistical significance is determined by examining the confidence interval thus studies with single estimates would not have a confidence interval in the context of out meta-analysis. Hence, we cannot indicate statistical significance for these studies.
[7] Cohen indicated that an effect can be referred to as a 'large effect' if its absolute value is greater than 0.4, a 'medium effect' if between 0.10 and 0.4 and 'small effect' if less than 0.10.

are reported. Of the nine reported estimates, only three present a statistically significant weighted average, which is negative. The overall effect of microcredit on income growth, drawn from nine estimates, is reported as -0.0263, which also reflects a weak effect.[8]

Ten studies with a total of 185 estimates are reported for the association between microcredit and consumption/expenditure. Of the reported 185 estimates, 62 estimates (33.51% of total estimates) are positive and statistically significant, while all other estimates are statistically insignificant. The overall fixed effect weighted average reported for all 185 estimates is 0.0147, which also represents a weak effect.

Two studies (Augsburg et al., 2012, Pitt and Khandker, 1998) with a total of 60 estimates report estimates on the impact of microcredit on labour supply. None presents a statistically significant weighted average. The overall weighted average for the estimates is -0.0018, which reflects no meaningful economic impact.

The effect of microcredit on business profits is reported by six primary studies (with a total of 17 estimates). Of the 17 estimates, 11 estimates (64.71% of the total estimates) are statistically insignificant, while other estimates are positive. Overall, the weighted average for all 17 estimates is 0.0268. Similarly, we find an overall effect of 0.0178, for microcredit's impact on business revenues. This estimate is drawn from four primary studies (nine estimates).

4.1.2. Impact of Access to Credit

Table 1B presents fixed effect weighted averages for the impacts of access to credit. Four studies (21 estimates) report on the impact of credit access on assets. We find that except for one study with eight estimates (Attanasio et al., 2011), which presents an insignificant average, all other studies suggest a positive and significant effect of credit access on assets. Further, the overall weighted average for all 21 estimates is 0.0180.

The association between access to credit and income is explained by 28 estimates, drawn from five primary studies. We find that all reported estimates are positive and significant, except for 8 estimates from one study (Attanasio et al., 2011), which shows a negative and significant weighted average, and 3 estimates from one study (Nghiem et al., 2012), which represent an insignificant weighted average. Overall, the weighted average calculated for this association is 0.0291. This suggests a weak positive effect of credit access on income.

With regards to impacts on consumption/expenditure, we report on nine studies (71 estimates). We find that 38 estimates (53.52% of the total estimates) present statistically insignificant averages while all other estimates are positive and statistically significant. Overall, the weighted average for all 71 estimates is 0.0233, which suggests a weak positive effect of credit access on consumption/expenditure.

[8] It must be note that this result emerges from a very small sample (drawn 3 studies) and thus the conclusion here as well as others drawn from three or less studies must be taken with caution. This also reveals the need for more empirical studies.

We find no significant association between access to credit and labour supply. This is based on evidence from only one study (Attanasio et al., 2011) with 16 estimates. Three studies with a total of 63 estimates report on the impacts of access to credit on business profits. Except for 16 estimates drawn from Attanasio et al. (2011), which present a negative and statistically significant weighted average, we find a positive weighted average for the remaining two studies. Furthermore, the overall weighted average for all 63 estimates is 0.0386. This indicates a weak positive effect on business profits. Similar findings are made for the relationship between access to credit and business revenues. Based on two primary studies with 13 total estimates, we find a positive effect on revenue, with a weighted average of 0.0739.

4.2. Genuine Effect beyond Bias

To determine if reported estimates are fraught with issues of publication selection bias, we first present funnel plots as shown in figures 1 to 11 to help visually inspect bias. A funnel plot is a scatter plot of effect size estimates against their precision. Usually, an observed symmetric inverted funnel shape of a funnel plot suggests that publication bias is unlikely (Egger et al., 1997). A visual inspection of figures 1 to 11 reveals signs of asymmetry in the funnel plots. This may suggest that publication bias is a threat in the microfinance impact literature however; a visual inspection alone is not a guarantee. Thus, we resort to a more thorough statistical test, which helps determine the direction and magnitude of bias, if any.

Hence, we conduct PET/FAT and PEESE analysis to examine the robustness of reported weighted averages to publication selection bias. These analyses are performed only for microfinance-poverty/microenterprise associations that have enough observations. For instance, the tests for 'genuine effect' beyond bias are not conducted for the association between access to credit and labour supply, which is reported on by only one primary study. We report estimates using weighted least squares (WLS), clustered data analysis (CDA) and mixed-effect linear model (MLM). CDA accounts for within-study variations and thus is used to obtain robust standard errors. We use MLM as our preferred estimation method since it accounts for both between and within study variations. PET/FAT and PEESE Results for microcredit and access to credit's impact are presented in tables 2A and 2B, respectively.

In addition, our preference would be to also conduct PET/FAT analysis for study clusters based on methodologies (study designs) used. For instance, put together studies that conduct randomised control trials (RCTs) in one category, quasi-experiments in another and possibly other 'observational data' in another category. However, issues of data limitation[9] would not permit this, and thus we control for study designs in our multivariate meta-regressions.

[9] There are six RCTs that examine one or more of the relationships we are interested in. However, at most, only two of such studies fall into the same cluster of interest. For instance, considering access to credit and assets, only Attanasio et al (2011) report on this relationship and it is impossible to perform a PET/FAT test for this study only. Overall, the total estimates from only RCTs examining a particular outcome (using a specific microfinance measure) are not enough for a separate PET/FAT analysis.

4.3. PET/FAT and PEESE Results

4.3.1. Impact of Microcredit

From table 2A, based on estimates from all estimation methods (WLS, CDA and MLM), we find that microcredit has a positive and significant effect on assets, with no evidence of publication bias. The effect size is 0.0697, which according to Cohen's guidelines is weak. This is consistent with findings presented by the fixed effect weighted average.

For the relationship between microcredit and income, PET/FAT results across all panels indicate no significant association. On the other hand, we find a negative and significant association between microcredit and income growth, with evidence of bias. Controlling for this bias, PEESE estimations (table 2A panel 4) also suggest a negative association; however, with a decrease in effect size. In the presence of bias, the effect size to be -0.2351, and this drops to -0.1265 after controlling for bias[10].

PET/FAT results for the entire sample suggest no significant relationship between microcredit and consumption/expenditure. These results are largely consistent with reported weighted averages, where close to 65% of reported estimates show statistically insignificant weighted averages. Similarly, we find that microcredit has no significant impact on labour supply, business profits and revenue. These findings are consistent across all estimation types (WLS, CDA and MLM).

4.3.2. Impact of Access to Credit

From table 2B, we find no significant association between access to credit and assets. Thus, overall, access to credit presents no significant effects on the assets of the poor. Similar insignificant results are observed for the effects of access to credit on consumption/expenditure as well as business revenue. These results do not differ significantly from reported weighted averages, which show effect size representing no meaningful economic impact.

Lastly, quite robustly, results across all estimation types indicate a positive association between access to credit and income. With no evidence of bias, the reported effect size is 0.0482. This represents a weak association and thus reflects no meaningful economic significance.

4.4. Meta-Regression Analysis

This section presents results from multivariate meta-regressions that include chosen moderating variables. We estimate MRA equation 13 and provide results for WLS, CDA and MLM. Our preferred model in this case is also the MLM. We run meta-regressions for studies that use microcredit only, and those that use access to credit only. The choices of moderating variables in our MRA are largely influenced by the factors likely to affect the effect estimates reported by the primary studies and also by the theoretical and empirical

[10] It should be noted that these results are based on only nine estimates.

assumptions and choices made by authors of individual primary studies. A list and descriptive statistics of moderating variables used is provided in table 3[11]. Results for the MRA are presented in tables 4A, 4B and 4C.

First we control for geographic location. It is observed that most of the primary studies examining the impact of microcredit consider case studies in Southeast Asia (see, e.g., Hoque (2004), McKernan (2002), Alam (2012), Garikipati (2008), and Imai and Azam (2012) among others). Therefore in the MRAs, we control for studies conducted with Southeast Asia as a case study to see if different estimates are obtained, leaving other geographic locations as base. From tables 4A and 4C, which explain the effects of microcredit on consumption/expenditure, and microcredit on income, respectively, our preferred estimation type (MLM) results reveal that the Southeast Asia dummy is insignificant. Thus, we conclude that geographic location does not affect the nature of estimates reported.

We also control for publication characteristics. First we control for publication type, and examine whether journal publications tend to report different estimates compared to working papers or theses. Controlling for publication type makes it possible to determine whether authors, as well as journal editors, are predisposed to publish papers with statistical significant estimates, consistent with theory, to justify selected models (Card and Krueger, 1995, Stanley, 2008, Ugur, 2013). We include a dummy for journal articles, leaving out working papers and theses as the base. From tables 4A and 4B, it is evident across all specification and estimation types that journal articles are predisposed to reporting slightly higher estimates for microcredit's and access to credit's impact on consumption/expenditure, respectively.

Furthermore, with regards to journal articles, we examine if the reported effect sizes vary depending on the publication outlet used. Thus, we control for high-ranked journals[12] to determine if the publication outlet used by authors presents any variations in reported effect sizes. We find that journal quality affects the nature of reported estimates. From table 4A, results show that high-ranked journals report higher effects on consumption/expenditure. We also note that high-ranked journals that report on the association between microcredit and income report slightly lower effect sizes (table 4C).

Lastly, on publication characteristics, we control for publication year to examine the nature of reported estimates, given that over time, studies with larger dataset and new methodologies have been published. Specifically, we control for studies published after 2005 because we observe that there is a significant increase in the number of publications after this date and

[11] Given that moderating variables represent variations in the literature, different moderating variables appear in different regressions. For instance, the relationship between microcredit and consumption/expenditure has the highest number of primary studies and reported estimates. Thus, there is a higher likelihood for more variations to exist in this cluster as opposed to the relationship between access to microcredit and consumption/expenditure, which has relatively fewer estimates. Also, some moderating variable are specific to the microfinance measure being used. For instance, productive loan amount can be controlled for in the MRA that involves microcredit studies but not in the access to credit studies. For this reason, there are moderating variables that appear in table 4B but are excluded from tables 4A and 4C, and vice versa. Additionally, given that estimates in some categories are very few, we are not able to conduct MRAs for all clusters. In the end, we ran MRAs for only the microcredit-consumption/expenditure, access to credit-consumption/expenditure and the microcredit-income associations.

[12] The Australian Business Dean's Council (ABDC) and the Australian Research Council (ARC) present classifications for journal quality. Journals are ranked in descending order of quality as A*, A, B and C. Thus, we introduce a dummy for A* and A ranked journals (high quality) in our MRA, and use other ranks as base.

these publications present analyses with richer datasets[13]. Based on MLM results we find no evidence of publication year affecting reported effect sizes, except for microcredit's effect on income (table 4C), where we find that studies published after 2005 tend to report lower effects on income.

Next, we control for study design and methodologies to examine what variations these categories of moderating variables may present. With regards to study designs, we control for RCTs and quasi-experiments, leaving out other study-types such as 'observational data' studies as the base. We find that the dummies for both RCTs and quasi-experiments are negative in the consumption/expenditure regression (table 4A). This suggests that study designs significantly affect reported effect sizes. Using ordinary least square (OLS) and instrumental variable (IV) techniques as controls, we also find that, from tables 4A and 4C, quite robustly, the econometric methodology adopted by primary studies affects the nature of reported estimates.

Lastly, in the category of study design, we control for data period and also examine if the length of intervention (short-term or long-term) has any significant effects on reported estimates. We find that studies that include data after 2000 in their analysis usually report lower effects of microcredit on income (table 4C), and also access to credit on consumption/expenditure (table 4B). With regards to length of intervention, we control for studies that examine the impact of short-term microfinance interventions. We find that studies that examine short-term interventions tend to report negative effects on consumption/expenditure. This is consistent with the arguments presented by Copestake et al. (2001) which suggest that clients become worse-off if they not remain in microcredit programmes for longer periods.

The last category of moderating variables capture microcredit programme intervention features as well as borrower characteristics. First, we control for female loans in the microcredit-consumption/expenditure specification, in order to examine if loans given to women affect effect sizes. This is relevant given arguments presented in favour of female borrowers. For instance, Garikipati (2008) argue that women are considered to be good credit risks and thus are less likely to misuse any credit they receive. Thus, some studies specifically target women while others separate outcomes by gender. In the case of the consumption/expenditure specification (table 4A), we find that the female loans dummy is insignificant. This suggests that giving loans to women does not significantly alter the level of individual or household consumption/expenditure.

We also control for loans given to borrowers below the poverty line and found that loans given to this category of borrowers negatively affects their consumption/expenditure level. However, based on the results from table 4C, we find that the loans given to borrowers below the poverty line positively affects their income. Interestingly, we find that productive loans

[13] Our meta-analysis includes publications from 1998 to 2013 (a period of 16 years). Fewer studies are published in the first eight years compared to the last eight. And most studies that fall in the category of the last eight years (after 2005) used larger panel datasets compared to previous studies, which in most cases used cross-sectional datasets.

do not affect the estimates reported for consumption/expenditure; however, they do positively affect income. These findings lend support to existing discussions that suggest that putting microloans into productive use positively impact microenterprise productivity, and subsequently income. We also introduce a dummy for borrowers that own an asset such as land. We examine if owning a piece of land alters the effects that access to credit has on consumption/expenditure. We find that the coefficient of land is not significant in the consumption/expenditure specification. This suggests that studies that capture borrowers with plots of land and have access to credit do not report results significant different from other studies.

Finally, we capture one important characteristic of microcredit programmes (i.e., whether loans are given to households or to individuals)[14]. Thus, we control for studies that report estimates on the effects of microfinance at the household level, with individual level as the base. We find that from tables 4A to 4C, all specification results indicate that studies that report effects at the household level tend to report positively on our outcome variables. Therefore, the evidence here suggests that microcredit given to households, and also household access to credit is more beneficial than individual level access. This is also the case for the effect of microcredit and income.

We now determine the net effect of microfinance on our outcome variables by examining the coefficient of the precision ($1/SE_{ri}$). After controlling for all relevant moderating variables, we find that there is no significant association between microcredit and consumption/expenditure (table 4A). Similar findings are made for access to microcredit and consumption/expenditure (table 4B). However, the net effect of microcredit on income after controlling for all moderating variable is positive with an effect size of 0.1537.

5. Robustness Checks

This section provides results from various checks that examine the robustness of our results. First, we observe that in a given cluster, weighted averages for some studies appear to be larger than those presented by other studies in that cluster. For instance, in table 1A, the weighted average from Li et al. (2011) that examines the impact of microcredit on income is 0.2425, which is relatively large compared to estimates from all the others studies. Thus, we exclude studies within each cluster that are relatively large to examine if the inclusion of these studies affect the overall weighted average.

Based on the robust check results presented in table 5, we observe that the exclusion of Li et al. (2011) from the microcredit-income and microcredit-consumption/expenditure clusters do not present significant variations in the overall weighted averages. For the microcredit-income association, the overall weighted average now observed is 0.0096 compared to the previously observed 0.0105. Similarly, for the microcredit-consumption/expenditure relationship, the new overall weighted average is 0.0144 which is not so different from the

[14] Ideally, another characteristic to capture is the lending type, whether primary studies examine individual lending or group lending. However, this is not possible given that for this dimension, fewer variations exist in the primary studies found in each microfinance-outcome variable cluster.

previously found 0.0147. Lastly, the exclusion of Berhane and Gardebroek (2011) which appears relatively large in the access to credit-consumption/expenditure cluster reveals no significant variations as well. The new and old overall weighted averages are 0.0203 and 0.0233, respectively.

Next, we present estimations for a smaller set of meta-observations. Although several estimates are presented by some primary studies, we extract a smaller set of meta-observation mainly consisting of primary studies authors' 'preferred' estimates and estimates capturing effect on 'total outcomes'. For instance, some studies provide a breakdown of consumption/expenditure such as food expenditure and other household expenditures, and examine effects on these consumption/expenditure types as well as on total consumption/expenditure. In the smaller set of observations used for our robustness check, we consider only estimates for total consumption/expenditure. Due to data limitations, this smaller set only exists for some microfinance-poverty/microenterprise associations. Results for these estimations are presented in tables 6A and 6B.

From table 6A, we find that our preferred estimation method results (MLM estimates) show that microcredit has no significant association with income, consumption/expenditure and also profits. This is consistent with the findings made from the larger sample. Thus, quite robustly, existing evidence suggests that microcredit has no significant impact on the outcomes measures income, consumption/expenditure and profits.

Turning to the results for access to credit (table 6B), we find that the effect of access to credit on assets and consumption/expenditure is consistent with findings from the larger sample where no significant association is observed. However, the effect on income is now insignificant in the smaller sample compared to the large sample which is positive but with a coefficient that represents a small effect.

Overall, results from our robustness checks largely confirm results presented for both the PET/FAT and fixed effect weighted averages.

6. Discussion and Conclusion

This study conducts a meta-analysis of the empirical literature that examines the impact of microfinance on poverty and microenterprises. We consider two measure of microfinance – microcredit and access to credit, and also seven measures of poverty and microenterprises namely consumption/expenditure, assets, income, income growth, labour supply, business profits and revenue. Based on 595 estimates reported by 25 primary studies, we examine the following four hypotheses: 1) Microcredit has a positive impact on poverty (H1); 2) Microcredit has a positive impact on microenterprises (H2); 3) Access to microcredit has a positive impact on poverty (H3); 4) Access to microcredit has a positive impact on microenterprises (H4). First, we report fixed effect weighted averages for each study that examines our relationships of interest. Second, using precision effect and funnel asymmetry tests (PET/FAT), we examine if reported effect sizes are fraught with issues of publication selection bias. Lastly, we conduct a multivariate meta-regression analysis (MRA) to model heterogeneity and examine if study, borrower and microfinance programme characteristics, amongst other things, affect the nature of reported effect sizes.

PET/FAT and MRA results do not support H1 for consumption/expenditure, given that we consistently find no significant effect of microcredit on consumption/expenditure. Similarly, considering our PET/FAT results, H1 is not supported for income however this finding is not robust to the inclusion of moderating variables given that MRA results indicate a positive effect of microcredit on income. H1 is however supported for assets considering our PET/FAT results. However, the effect size, 0.0716, is too small to have any meaningful economic impact. PET/FAT results and fixed effects weighted averages show a negative effect of microcredit on income growth and thus we conclude that H1 is not supported in the case of income growth. Considering assets and consumption/expenditure, our results do not support H3. However, quite robustly, results support H3 for income.

Our results do not support H2 for any of the microenterprise measures. This finding is consistent across both the fixed effect weighted average and PET/FAT results. Thus, overall, we find that microcredit has no significant impact on microenterprises (labour supply, business profits and revenues). This is also the case for access to credit and thus H4 is also not supported.

Our results are consistent with recent systematic reviews such as Duvendack et al. (2011) that report no significant effect of microfinance on economic outcomes. Therefore, there appears to be no strong evidence, at the moment, to support the existing claims that microfinance has a positive effect on the well-being of the poor as well as their businesses. The mainly insignificant impact of microcredit could be as a result of the long loan-repayment time. Stewart et al. (2012) argue that, eventually, microcredit is likely to increase income however, given that borrowers incur debts which must be repaid overtime, expected positive impacts of microcredit on some economic outcomes may not be immediate. The positive impact of microcredit on assets is somewhat expected. In theory, microcredit is expected to increase the assets of borrowers, especially for use in the development of microenterprises. However, overtime, the burden of loan repayments may compel borrowers to sell assets in order to pay loans quickly. This phenomenon could explain the observed weak impact.

Of course, these conclusions have been drawn from evidence that consider only microcredit and access to credit. Perhaps, the implementation of other microfinance products might play a role in enhancing the effectiveness of microcredit. Within, the microfinance sector, it appears the hype has been on microcredit and various lending schemes, and this has likely diverted the attention from other microfinance products as well as other potential development programmes. Arguments presented by some studies (Collins et al., 2009, Duvendack et al., 2011) suggest that the poor do not only require credit but also other financial services such as insurance and savings, as well as technical support. Several microfinance institutions provide these services and it would be worthwhile to consider the impact of microfinance more holistically.

We concur with Duvendack et al. (2011) and propose the need for more and better research that focus on the impact of microcredit, and also on the other dimensions of microfinance. In addition, for researchers to be able to design better empirical studies there is a need for more robust and stronger theoretical motivations, which, at the moment, are relatively scarce as well. As it stands, hypotheses formulation is quite difficult given that the pathways through which microfinance can impact social and economic outcomes are complex and quite ambiguous (Levine, 2004, Korth et al., 2012). At the moment, most theories surrounding microfinance assume that a client's ability to borrow depends on the capacity of potential or actual business revenue to meet credit costs. A course of future theoretical research would be to also account, more clearly, for individual and business vulnerabilities and risk, and how these affect the ability to borrow.

With regards to potential sources of heterogeneity in reported estimates, we find that differences in primary studies affect reported effect size. Specifically, we find that study design, borrower and microcredit programme characteristics, as well as sample and data characteristics all affect the microfinance-poverty/microenterprises relationship. A number of reasons could explain the conflicting results across time periods, microcredit programme types and sample settings. While we provide some explanations in the section 4.4, it would be worthwhile to examine in more details, from a theoretical perspective, how these factors influence the impact of microfinance. Thus, a course of future research can be to provide more robust discussions of theories that explain the sources of heterogeneity. Evidence from our study also shows that short-term impacts of microfinance are detrimental. A course of future research is to focus more on the long-term impact of microfinance. This is crucial given that investment into some category of microenterprises do no yield immediate returns. Thus, individuals could channel funds into investments early on, with that investment translating into increased consumption much later. This cannot be captured effectively if studies do not consider data periods sufficiently long enough. Nonetheless, this does not undermine the importance of studies that consider the short-term impact of microfinance. Some microfinance clients drop out along the line and this short-term intervention is likely to impact positively or negatively on the well-being of such clients. Thus, it is also worthwhile to examine, more thoroughly, the short-term impact of microfinance as well. In brief, there is a need to conduct more primary research, both theoretical and empirical, to understand how microfinance works and the channels through which it can affect the well-being of the poor.

A number of policy relevant suggestions also emerge. Although we find no strong evidence of microfinance been detrimental to the well-being and businesses of the poor, we also find no evidence of a strong positive impact. However, evidence of negative impact, for instance observed impact on income growth, suggests that microfinance poses the risk of worsening the plight of the poor. Stewart et al. (2012) indicate that, in some cases, microcredit brings the risk of collateral lost and increased debt. Thus, the question of whether microfinance is a viable development tool in improving the well-being of the poorest of the poor needs to be revisited and considered seriously. Furthermore, evidence from our MRA suggests that microcredit worsens the plight of borrowers below the poverty line, with regards to consumption/expenditure. This raises some major concerns, and thus caution needs to be taken in providing microloans to the poorest of the poor. Specifically, the target of microfinance services should not just be to promote financial inclusion but to also consider carefully the implications of services delivered to the very poor, in terms of potential negative effects on well-being and increased debt. Stewart et al. (2012) propose that there is less risk of microcredit causing harm if services are targeted at clients with some level of financial security, or perhaps other sources of income, which makes it possible and easier to repay loans. However, such category of clients would not be the poorest of the poor in society and this brings to question the validity of microfinance as a development tool in addressing issues of severe poverty. Related to this, Zeller et al. (2001) indicate that access to credit can reduce the management of risk through the diversification of livelihoods and this subsequently raises income. However, this may also not be very applicable in the case of the poorest, as they are not usually skilled enough.

Overall, our findings indicate that when the evidence base in a research area is too broad to allow general conclusions, meta-analysis is effective in synthesizing the evidence and accounting for heterogeneity and bias, thus leading to a general conclusion. We are faced with a number of shortcomings and challenges. These are mostly with regards to the evidence base. First, we find that there is a significant lack of empirical evidence on the impact of microfinance. Furthermore, we find that the evidence on the impact of microfinance on poverty and microenterprise is characterised by a high level of heterogeneity. This includes study design, intervention types, sample, as well as outcome variables and covariates used in primary studies. While, there are several indicators which can potentially be affected by microfinance interventions, it is in the best interest of future research and also practitioners to identify key variables (or indices), and set standards that can be used to determine the success or failure of microfinance interventions. Related to this, the measurement of income, consumption/expenditure and other economic outcomes in countries with large agricultural sectors and other informal enterprises is likely to be affected by measurement error. This measurement error could be time-varying and can potentially impact on estimates of the dynamics of such economic outcomes. A relevant course of future research would be to examine the measurement error in economic outcomes and how it impacts estimates in impact studies, especially in the context of microfinance.

Lastly, the reliability of our meta-analysis may be questioned given the arguments in the mainstream against some of the included studies. Although it is true that a number of studies included in our meta-analysis have been criticised extensively, especially in term of methodology used and problems of replication (for instance, Pitt and Khandker (1998)), these studies form part of the evidence base and appear to be, perhaps, the most authoritative studies in the area of microfinance impact studies. Thus, the exclusion of such studies would be more prejudicial to our study, and would also not reflect the overall evidence base. A major limitation of this study concerns the relatively few studies that exist making it difficult to run PET/FAT and MRAs for all clusters of our microfinance and outcome variables. Furthermore, it is likely some relevant studies are published in languages other than English and may not be indexed in search databases, thus, making it difficult to find these studies

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TABLES

Table 1A - Impact of Microcredit
(Overview of Evidence Base per Study - Simple & Fixed Effect Weighted Means)

Paper	No. of Estimates	Simple Mean	Weighted Mean (FE)	Significance	Confidence Interval
Impact on Assets					
Cotler and Woodruff (2008)	6	0.0755	0.0767	Yes	(0.0547, 0.0986)
Garikipati (2008)	1	0.0829	0.0829		
Pitt and Khandker (1998)	30	0.0415	0.0408	Yes	(0.0273, 0.0544)
Takahashi et al. (2010)	6	-0.1089	-0.1097	Yes	(-0.1776, -0.0417)
	43	***0.0262***	***0.0429***		
Impact on Income					
Abou-Ali et al. (2009)	5	-0.0397	-0.0428	No	(-0.1166, 0.0310)
Copestake et al. (2005b)	2	0.1069	0.1069	Yes	(0.0568, 0.1571)
Cotler and Woodruff (2008)	3	0.0433	0.0387	No	(-0.0406, 0.1181)
Cuong (2008)	4	0.0362	0.0351	Yes	(0.0057, 0.0646)
Imai and Azam (2012)	13	0.0097	0.0076	No	(-0.0060, 0.0212)
Kaboski and Townsend (2012)	26	-0.0097	0.0063	No	(-0.0102, 0.0227)
Kouassi (2008)	4	0.0649	0.0431	Yes	(0.0019, 0.0843)
Li et al. (2011)	1	0.2425	0.2425		
Takahashi et al. (2010)	2	0.0600	0.0600	No	(-0.0599, 0.1799)
	60	***0.0131***	***0.0105***		
Impact on Income Growth					
Copestake (2002)	4	0.0766	0.0571	No	(-0.0858, 0.2001)
Copestake et al. (2001)	2	-0.0355	-0.0360	No	(-1.1040, 1.0320)
Copestake et al. (2005b)	3	-0.0678	-0.0674	Yes	(-0.0880, -0.0468)
	9	***0.0036***	***-0.0263***		
Impact on Consumption/ Expenditure					
Abou-Ali et al. (2009)	15	0.0222	0.0066	No	(-0.0410, 0.0543)
Alam (2012)	77	0.0081	0.0081	No	(-0.0013, 0.0176)
Augsburg et al. (2012)	5	-0.0257	-0.0257	No	(-0.0556, 0.0041)
Cuong (2008)	4	0.0426	0.0416	Yes	(0.0131, 0.0702)
Imai and Azam (2012)	9	0.0259	0.0230	Yes	(0.0115, 0.0346)
Islam (2009)	18	0.0141	0.0054	No	(-0.0095, 0.0203)
Kaboski and Townsend (2012)	24	0.0158	0.0158	Yes	(0.0099, 0.0217)
Li et al. (2011)	1	0.2556	0.2556		
Pitt and Khandker (1998)	24	0.0239	0.0237	Yes	(0.0130, 0.0344)
Takahashi et al. (2010)	8	0.0481	0.0487	No	(-0.0672, 0.1647)
	185	***0.0167***	***0.0147***		
Impact on Labour Supply					
Augsburg et al. (2012)	7	0.0213	0.0214	No	(-0.0322, 0.0750)
Pitt and Khandker (1998)	53	-0.0003	-0.0021	No	(-0.0134, 0.0092)
	60	***0.0022***	***-0.0018***		
Impact on Business Profits					
Augsburg et al. (2012)	1	0.0506	0.0506		
Copestake et al. (2001)	2	0.2310	0.2353	No	(-0.9506, 1.4212)
Copestake et al. (2005b)	1	-0.0459	-0.0459		
Cotler and Woodruff (2008)	3	0.0648	0.0618	No	(-0.0021, 0.1258)
Kaboski and Townsend (2012)	4	0.0185	0.0185	Yes	(0.0009, 0.0362)
Takahashi et al. (2010)	6	0.0332	0.0339	No	(-0.0684, 0.1363)
	17	***0.0550***	***0.0268***		
Impact on Revenue					
Augsburg et al. (2012)	1	0.0575	0.0575		
Copestake et al. (2005b)	1	0.0003	0.0003		
Kaboski and Townsend (2012)	1	0.0077	0.0077		
Takahashi et al. (2010)	6	0.0394	0.0406	No	(-0.0689, 0.1501)
	9	***0.0336***	***0.0178***		

Table 1B - Impact of Access to Credit
(Overview of Evidence Base per Study - Simple & Fixed Effect Weighted Means)

Paper	No. of Estimates	Simple Mean	Weighted Mean (FE)	Significance	Confidence Interval
Impact on Assets					
Attanasio et al. (2011)	8	-0.0131	-0.0131	No	(-0.0689, 0.1501)
Garikipati (2008)	1	0.0534	0.0534		
Gertler et al. (2009)	6	0.0246	0.0246	Yes	(0.0106, 0.0386)
Islam (2011)	6	0.0482	0.0458	Yes	(0.0328, 0.0588)
	21	***0.0184***	***0.0180***		
Impact on Income					
Attanasio et al. (2011)	8	-0.0115	-0.0115	Yes	(-0.0189, -0.0041)
Cuong (2008)	4	0.0394	0.0383	Yes	(0.0041, 0.0724)
Islam (2011)	12	0.0458	0.0465	Yes	(0.0290, 0.0639)
Li et al. (2011)	1	0.0550	0.0545		
Nghiem et al. (2012)	3	-0.0108	-0.0108	No	(-0.1638, 0.1423)
	28	***0.0228***	***0.0291***		
Impact on Consumption/ Expenditure					
Attanasio et al. (2011)	8	0.0216	0.0216	Yes	(0.0133, 0.0300)
Banerjee et al. (2009)	23	0.0118	0.0093	No	(-0.0027, 0.0212)
Berhane and Gardebroek (2011)	8	0.1136	0.1604	Yes	(0.0218, 0.2990)
Cuong (2008)	4	0.0424	0.0415	Yes	(0.0152, 0.0679)
Gertler et al. (2009)	9	0.0299	0.0299	Yes	(0.0154, 0.0444)
Hoque (2004)	3	0.0764	0.0764	Yes	(0.0196, 0.1332)
Islam (2011)	12	0.0394	0.0476	No	(-0.0107, 0.1059)
Li et al. (2011)	1	0.0340	0.0340		
Nghiem et al. (2012)	3	-0.0358	-0.0376	No	(-0.3912, 0.3160)
	71	***0.0341***	***0.0233***		
Impact on Labour Supply					
Attanasio et al. (2011)	16	-0.0015	-0.0015	No	(-0.0100, 0.0070)
Impact on Business Profits					
Attanasio et al. (2011)	16	-0.0101	-0.0102	Yes	(-0.0160, -0.0044)
Banerjee et al. (2009)	1	0.0486	0.0486		
McKernan (2002)	46	0.0600	0.0589	Yes	(0.0404, 0.0774)
	63	***0.0420***	***0.0386***		
Impact on Revenue					
Banerjee et al. (2009)	1	0.0288	0.0288		
Kevane and Wydick (2001)	12	0.1197	0.1089	Yes	(0.0569, 0.1607)
	13	***0.1127***	***0.0739***		

Table 2A - Impact of Microcredit (PET/FAT and PEESE Results)

Panel 1 - WLS Estimations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Assets	Income	Income Growth	Con/Exp	Labour Supply	Profits	Revenue
Precision (β_0)	0.0697***	0.0037	-0.2351**	0.0090	-0.0265	0.0054	0.0013
	(0.0187)	(0.0104)	(0.0843)	(0.0112)	(0.0224)	(0.0168)	(0.0256)
Bias (α_0)	-1.0185	0.4815	4.6069**	0.3479	1.9131	1.0459	0.4275
	(0.6732)	(0.6398)	(1.8015)	(0.6551)	(1.6800)	(0.6491)	(0.5444)
Observations	43	60	9	185	60	17	9
R-squared	0.2532	0.0022	0.5265	0.0035	0.0237	0.0069	0.0004

Panel 2 – CDA Estimations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Assets	Income	Income Growth	Con/Exp	Labour Supply	Profits	Revenue
Precision (β_0)	0.0697*	0.0037	-0.2351**	0.0090	-0.0265	0.0054	0.0013
	(0.0243)	(0.0106)	(0.0440)	(0.0142)	(0.0264)	(0.0148)	(0.0095)
Bias (α_0)	-1.0185	0.4815	4.6069*	0.3479	1.9131	1.0459	0.4275**
	(0.9637)	(0.7246)	(1.3078)	(0.8187)	(2.1035)	(0.9566)	(0.1136)
Observations	43	60	9	185	60	17	9
R-squared	0.2532	0.0022	0.5265	0.0035	0.0237	0.0069	0.0004

Panel 3 – MLM Estimations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Assets	Income	Income Growth	Con/Exp	Labour Supply	Profits	Revenue
Precision (β_0)	0.0716***	0.0027	-0.2351***	0.0059	-0.0265	-0.0046	0.0013
	(0.0266)	(0.0120)	(0.0743)	(0.0117)	(0.0220)	(0.0289)	(0.0226)
Bias (α_0)	-0.9323	1.3551	4.6069***	0.6015	1.9131	1.4319	0.4275
	(0.8363)	(0.9656)	(1.5888)	(0.6913)	(1.6517)	(1.0787)	(0.4801)
Observations	43	60	9	185	60	17	9

Panel 4 - PEESE Estimations (Income Growth)

	(1)	(2)	(3)
VARIABLES	WLS	CDA	MLM
Precision (β_0)	-0.1265**	-0.1265***	-0.1265***
	(0.0424)	(0.0026)	(0.0374)
Standard error (α_0)	45.7769**	45.7769**	45.7769***
	(16.9981)	(8.0573)	(14.9909)
Observations	9	9	9

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2B – Impact of Access to Credit (PET/FAT Results)

Panel 1 - WLS Estimations

	(1)	(2)	(3)	(4)
VARIABLES	Assets	Income	Con/Exp	Revenue
Precision (β_0)	0.0282	0.0556***	-0.0021	-0.0079
	(0.0275)	(0.0193)	(0.0155)	(0.0381)
Bias (α_0)	-0.5073	-1.3989	1.6122*	1.8729**
	(1.3365)	(0.9696)	(0.9089)	(0.7784)
Observations	21	28	71	13
R-squared	0.0525	0.2415	0.0003	0.0039

Panel 2 – CDA Estimations

	(1)	(2)	(3)	(4)
VARIABLES	Assets	Income	Con/Exp	Revenue
Precision (β_0)	0.0282	0.0556***	-0.0021	-0.0079
	(0.0228)	(0.0069)	(0.0158)	(0.0051)
Bias (α_0)	-0.5073	-1.3989	1.6122	1.8729**
	(1.6767)	(0.9635)	(0.8757)	(0.0777)
Observations	21	28	71	13
R-squared	0.0525	0.2415	0.0003	0.0039

Panel 3 - MLM Estimations

	(1)	(2)	(3)	(4)
VARIABLES	Assets	Income	Con/Exp	Revenue
Precision (β_0)	0.0036	0.0482**	0.0033	-0.0079
	(0.0222)	(0.0229)	(0.0166)	(0.0351)
Bias (α_0)	0.7521	-1.0444	1.3698	1.8729***
	(1.0608)	(1.1680)	(0.9476)	(0.7160)
Observations	21	28	71	13

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3 – Summary/Descriptive Statistics (MRA Variables)

Variables	Definition	Percent of 1s	MC	AM
RCT	1 if PS uses an RCT, otherwise 0	20.85%	3.55%	44.77%
Quasi-experiment	1 if PS uses a quasi-experiment, otherwise 0	38.41%	61.23%	6.86%
OLS	1 if PS uses OLS estimation method, otherwise 0.	20.03%	23.18%	15.68%
IV	1 if PS uses an IV estimation method, otherwise 0.	23.87%	33.57%	10.46%
Household Level	1 if PS examines impact at household level, otherwise 0	13.31%	18.68%	5.88%
Female	1 if PS reports impact of female loan, otherwise 0	20.58%	29.55%	8.17%
Below Poverty Line	1 if PS examines impact on clients below poverty line, otherwise 0	3.07%	4.96%	1.96%
Productive Loan	1 if PS reports impact of productive loans, otherwise 0	5.08%	8.75%	0%
Land	1 if PS captures borrowers with Land, otherwise 0	9.33%	0%	22.22%
Individual Lending	1 if PS examines impact of individual lending, otherwise 0	4.39%	0%	10.46%
Data Period	1 if PS includes data from 2000, otherwise 0	35.12%	24.11%	50.33%
Southeast Asia	1 if PS includes data from Southeast Asia, otherwise 0	69.82%	82.03%	52.94%
Short term	1 if PS examines short-term impact of microfinance, otherwise 0	55.83%	55.79%	55.88%
Journal Rank	1 if PS is published in high-ranked journal, otherwise 0	39.64%	43.03%	34.97%
Journal	1 if PS is a journal paper, otherwise 0	73.25%	84.16%	58.17%
Publication Year	1 if PS is published after 2005, otherwise 0	57.48%	48.23%	70.26%

All variables are divided by SE_{ri}

*PS means primary study

*MC - Microcredit *AM - Access to Microcredit

Table 4A – MRA (Microcredit and Consumption/Expenditure)

	(1)	(3)	(7)
VARIABLES	WLS	CDA	MLM
Precision	0.0166	0.0166	0.0166
	(0.0429)	(0.0245)	(0.0411)
OLS	0.0054	0.0054***	0.0054
	(0.0139)	(0.0014)	(0.0133)
IV	0.0155	0.0155***	0.0155*
	(0.0190)	(0.0034)	(0.0182)
Journal Rank	0.1895**	0.1895***	0.1895**
	(0.0861)	(0.0340)	(0.0825)
Household Level	0.1534*	0.1534***	0.1534*
	(0.0886)	(0.0402)	(0.0850)
Journal	0.0534*	0.0534***	0.0534**
	(0.0279)	(0.0112)	(0.0267)
Southeast Asia	-0.0462	-0.0462***	-0.0462
	(0.0487)	(0.0132)	(0.0467)
Female Loans	0.0032	0.0032	0.0032
	(0.0095)	(0.0141)	(0.0091)
Below Poverty Line	-0.0166	-0.0166***	-0.0166*
	(0.0200)	(0.0022)	(0.0191)
Productive Loan	-0.0229	-0.0229***	-0.0229
	(0.0247)	(0.0000)	(0.0236)
RCT	-0.0940*	-0.0940**	-0.0940*
	(0.0537)	(0.0401)	(0.0515)
Quasi-experiment	-0.2170**	-0.2170***	-0.2170***
	(0.0857)	(0.0356)	(0.0821)
Data Period	-0.0056	-0.0056	-0.0056
	(0.0279)	(0.0070)	(0.0267)
Publication Year	-0.0165	-0.0165**	-0.0165
	(0.0162)	(0.0058)	(0.0155)
Constant	1.6309*	1.6309	1.6309**
	(0.8473)	(1.4812)	(0.8122)
Observations	185	185	185

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4B – MRA (Access to Microcredit and Consumption/Expenditure)

	(2)	(4)	(10)
VARIABLES	WLS	CDA	MLM
Precision	0.2501	0.2501	0.2501
	(0.1602)	(0.1724)	(0.1509)
Household Level	0.1049	0.1049**	0.1049*
	(0.0629)	(0.0360)	(0.0592)
Journal	0.0557***	0.0557**	0.0557***
	(0.0202)	(0.0167)	(0.0191)
Publication Year	-0.2067	-0.2067	-0.2067
	(0.1467)	(0.1410)	(0.1382)
Short Term	-0.0309	-0.0309*	-0.0309*
	(0.0248)	(0.0158)	(0.0233)
Data period	-0.0271	-0.0271***	-0.0271**
	(0.0232)	(0.0063)	(0.0218)
Land	0.0399	0.0399	0.0399
	(0.0675)	(0.0617)	(0.0636)
Constant	-2.4001	-2.4001	-2.4001*
	(1.4964)	(2.3419)	(1.4096)
Observations	71	71	71

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4C – MRA (Microcredit and Income)

VARIABLES	(1) WLS	(2) CDA	(3) MLM
Precision	0.1537**	0.1537***	0.1537***
	(0.0618)	(0.0171)	(0.0553)
OLS	0.0639***	0.0639***	0.0639***
	(0.0172)	(0.0015)	(0.0154)
IV	0.0670***	0.0670***	0.0670***
	(0.0181)	(0.0019)	(0.0162)
Journal Rank	-0.0961***	-0.0961***	-0.0961***
	(0.0232)	(0.0037)	(0.0207)
Household Level	0.3119***	0.3119***	0.3119***
	(0.0752)	(0.0143)	(0.0672)
Journal	-0.0187	-0.0187	-0.0187
	(0.0332)	(0.0142)	(0.0297)
Southeast Asia	0.0407	0.0407**	0.0407
	(0.0319)	(0.0153)	(0.0286)
Below Poverty Line	0.0174	0.0174***	0.0174*
	(0.0260)	(0.0010)	(0.0233)
Productive Loan	0.0349**	0.0349***	0.0349***
	(0.0143)	(0.0002)	(0.0128)
Data Period	-0.0307	-0.0307***	-0.0307*
	(0.0183)	(0.0017)	(0.0164)
Publication Year	-0.1764***	-0.1764***	-0.1764***
	(0.0588)	(0.0142)	(0.0526)
Constant	0.0786	0.0786	0.0786
	(0.6122)	(0.4931)	(0.5475)
Observations	60	60	60

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5 Fixed-Effect Weighted Averages (Robust Check)

Paper	No. of Estimates	Simple Mean	Weighted Mean	Significance	Confidence Interval
Impact of Microcredit on Income					
Abou-Ali et al. (2009)	5	-0.0397	-0.0428	No	(-0.1166, 0.0310)
Copestake et al. (2005b)	2	0.1069	0.1069	Yes	(0.0568, 0.1571)
Cotler and Woodruff (2008)	3	0.0433	0.0387	No	(-0.0406, 0.1181)
Cuong (2008)	4	0.0362	0.0351	Yes	(0.0057, 0.0646)
Imai and Azam (2012)	13	0.0097	0.0076	No	(-0.0060, 0.0212)
Kaboski and Townsend (2012)	26	-0.0097	0.0063	No	(-0.0102, 0.0227)
Kouassi (2008)	4	0.0649	0.0431	Yes	(0.0019, 0.0843)
Takahashi et al. (2010)	2	0.0600	0.0600	No	(-0.0599, 0.1799)
	59	***0.0092***	***0.0096***		
Impact of Microcredit on Consumption/ Expenditure					
Abou-Ali et al. (2009)	15	0.0222	0.0066	No	(-0.0410, 0.0543)
Alam (2012)	77	0.0081	0.0081	No	(-0.0013, 0.0176)
Augsburg et al. (2012)	5	-0.0257	-0.0257	No	(-0.0556, 0.0041)
Cuong (2008)	4	0.0426	0.0416	Yes	(0.0131, 0.0702)
Imai and Azam (2012)	9	0.0259	0.0230	Yes	(0.0115, 0.0346)
Islam (2009)	18	0.0141	0.0054	No	(-0.0095, 0.0203)
Kaboski and Townsend (2012)	24	0.0158	0.0158	Yes	(0.0099, 0.0217)
Pitt and Khandker (1998)	24	0.0239	0.0237	Yes	(0.0130, 0.0344)
Takahashi et al. (2010)	8	0.0481	0.0487	No	(-0.0672, 0.1647)
	184	***0.0154***	***0.0144***		
Impact of Access to Microcredit on Consumption/ Expenditure					
Attanasio et al. (2011)	8	0.0216	0.0216	Yes	(0.0133, 0.0300)
Banerjee et al. (2009)	23	0.0118	0.0093	No	(-0.0027, 0.0212)
Cuong (2008)	4	0.0424	0.0415	Yes	(0.0152, 0.0679)
Gertler et al. (2009)	9	0.0299	0.0299	Yes	(0.0154, 0.0444)
Hoque (2004)	3	0.0764	0.0764	Yes	(0.0196, 0.1332)
Islam (2011)	12	0.0394	0.0476	No	(-0.0107, 0.1059)
Li et al. (2011)	1	0.0340	0.0340		
Nghiem et al. (2012)	3	-0.0358	-0.0376	No	(-0.3912, 0.3160)
	71	***0.0239***	***0.0203***		

Table 6A - Impact of Microcredit (Robustness Check)

Panel 1 - WLS Estimations

VARIABLES	(1) Income	(2) Con/Exp	(3) Profits
Precision (β_0)	0.0162*	0.0248***	0.0143
	(0.0094)	(0.0086)	(0.0099)
Bias (α_0)	1.3876**	0.0160	0.5419
	(0.5602)	(0.4621)	(0.4083)
Observations	25	85	14
R-squared	0.1148	0.0905	0.1476

Panel 2 – CDA Estimations

VARIABLES	(1) Income	(2) Con/Exp	(3) Profits
Precision (β_0)	0.0162*	0.0248**	0.0143
	(0.0075)	(0.0082)	(0.0082)
Bias (α_0)	1.3876*	0.0160	0.5419
	(0.6136)	(0.4770)	(0.4915)
Observations	25	85	14
R-squared	0.1148	0.0905	0.1476

Panel 3 – MLM Estimations

VARIABLES	(1) Income	(2) Con/Exp	(3) Profits
Precision (β_0)	0.0133	-0.0290	0.0130
	(0.0097)	(0.0207)	(0.0109)
Bias (α_0)	1.8217**	3.0586***	0.6336
	(0.7196)	(1.1472)	(0.4576)
Observations	25	85	14

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6B – Impact of Access to Credit (Robustness Check)

Panel 1 - WLS Estimations

	(1)	(2)	(3)	(4)
VARIABLES	Assets	Income	Con/Exp	Profits
Precision (β_0)	0.0416	0.0686**	0.0336	-0.7858***
	(0.0260)	(0.0249)	(0.0292)	(0.1426)
Bias (α_0)	-1.5067	-2.3191	1.1970	35.6241***
	(1.2833)	(1.3530)	(1.3483)	(6.3065)
Observations	17	18	31	23
R-squared	0.1457	0.3220	0.0437	0.5913

Panel 2 – CDA Estimations

	(1)	(2)	(3)	(4)
VARIABLES	Assets	Income	Con/Exp	Profits
Precision (β_0)	0.0416	0.0686**	0.0336	-0.7858
	(0.0429)	(0.0208)	(0.0186)	(0.2890)
Bias (α_0)	-1.5067	-2.3191	1.1970	35.6241
	(2.2918)	(1.8008)	(0.6503)	(12.4984)
Observations	17	18	31	23
R-squared	0.1457	0.3220	0.0437	0.5913

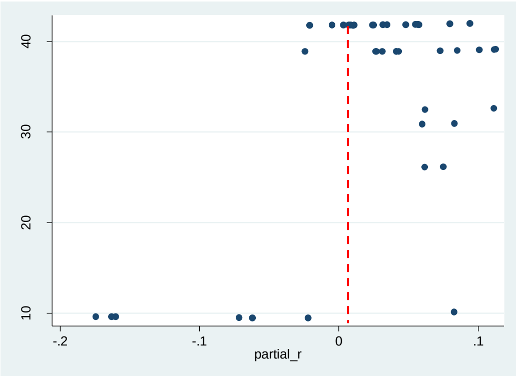
Panel 3 - MLM Estimations

	(1)	(2)	(3)	(4)
VARIABLES	Assets	Income	Con/Exp	Profits
Precision (β_0)	0.0203	0.0394	0.0408	-0.5049*
	(0.0287)	(0.0312)	(0.0313)	(0.2751)
Bias (α_0)	-0.0278	-0.4233	0.8650	24.5067**
	(1.3247)	(1.6076)	(1.4814)	(12.2986)
Observations	17	18	31	23

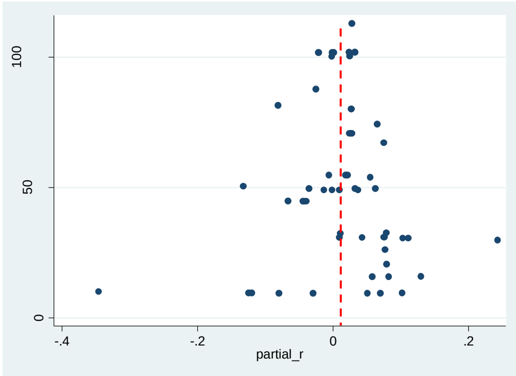
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figures 1 to 11 – Funnel Plots

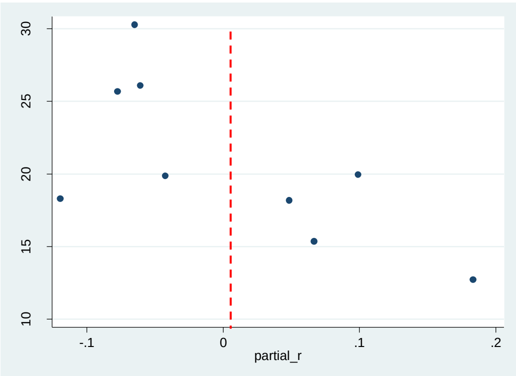
(1) Microcredit & Assets



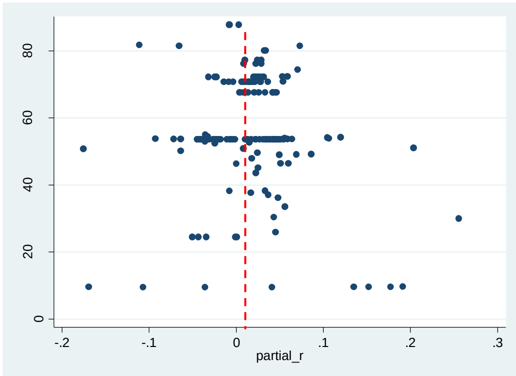
(2) Microcredit & Income



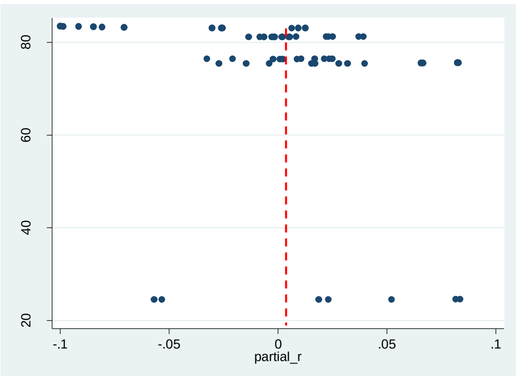
(3) Microcredit & Income Growth



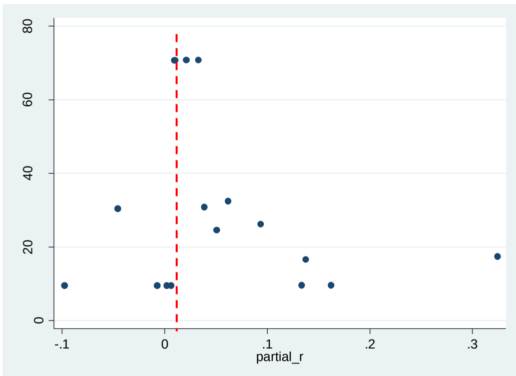
(4) Microcredit & Con/Exp



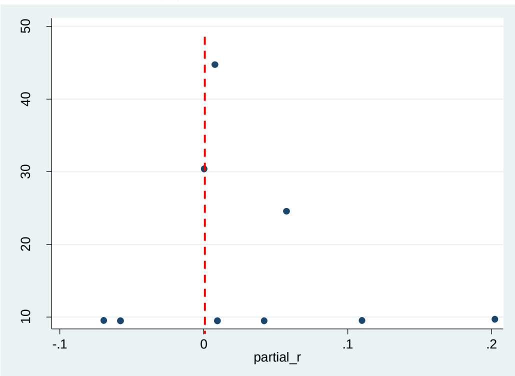
(5) Microcredit & Labour Supply



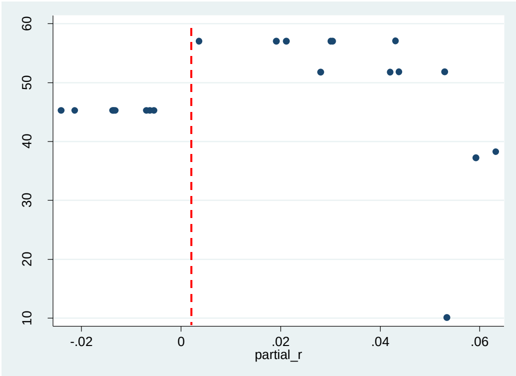
(6) Microcredit & Profits



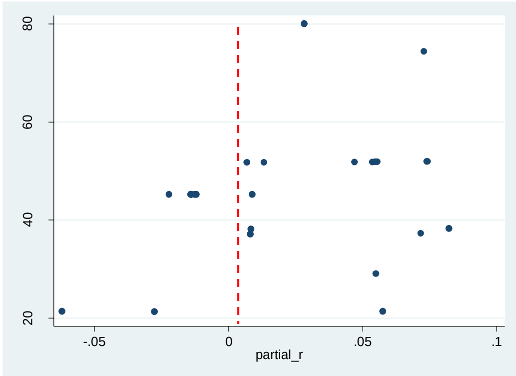
(7) Microcredit & Revenue



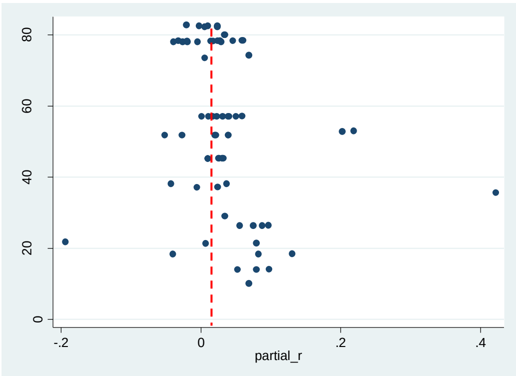
(8) Access to Credit & Assets



(9) Access to Credit & Income



(10) Access to Credit & Con/Exp



(11) Access to Credit & Revenue