Impact of Microfinance on Female Empowerment: A Review of the Empirical Literature

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Abstract
Microfinance is considered a major development tool in most developing countries. Specifically, its interventions have been targeted towards women as an empowerment tool. However, recent systematic reviews report on an inconclusive impact of microfinance on female empowerment. We conduct a meta-analysis of the impact of microfinance on five measures of female empowerment used in the empirical literature, namely mobility, decision-making power, control over finance, awareness and women’s assets. We find no evidence of a meaningfully positive impact of microfinance on female empowerment. This is evident from all three meta-analysis tools used - fixed effects weighted averages, precision effect and funnel asymmetry tests (PET/FAT), and also the multivariate meta-regression analysis (MRA).

Keywords – Microfinance, Empowerment, Meta-analysis
JEL Codes: G21
1. Introduction

Microfinance is the provision of small-scale financial services and products to poor individuals and households. The central idea is to serve low-income households with the aim of improving their quality of life. The microfinance industry has grown very rapidly in recent years as it has become part of the economic growth orthodoxy mainly in developing countries. Like other pertinent issues that have caught the attention of several academics, stakeholders and policy makers, microfinance has become the centre of various intense debates and public discourse.

The emergence of microfinance came with the promise of poverty alleviation and the primary aim of providing financial services to the poor. In general, the industry professes a promise of reducing poverty, increasing productivity and income amongst the low-income households as well as a long term benefit of welfare improvement amongst other things (Armendariz & Morduch, 2010; Torre & Vento, 2006). According to Heen (2004), the client-base of microfinance institutions (MFIs) includes mostly females, retrenched workers, peasant farmers and micro-entrepreneurs all of whom fall into various poverty levels and benefit from the various services of microfinance.

As a major development tool, the initial emphasis of the industry on poverty alleviation has changed and expectations for the industry have heightened. It has been acknowledged that, in poor economies, women are more likely to be constrained credit wise and also have limited access to the wage labour market (Pitt, Khandker, & Cartwright, 2006). Thus, most MFIs attempt to pay more attention to female clients with the hope of empowering them (Mayoux, 2001). It is expected that targeting microfinance programs towards women would empower them in various aspects of their lives. More so, women are considered to be good credit risks (Supriya Garikipati, 2008) and thus are less likely to misuse any credit they receive.
These promises and expectations have inspired various studies with the primary focus of examining the impact of microfinance interventions on female empowerment. However, this evidence base is accompanied by a high level of heterogeneity, especially due to the different proxies for female empowerment that exist. This makes it difficult to draw a general conclusion on the effects of microfinance on female empowerment.

Recent systematic reviews such as Duvendack et al. (2011), Stewart, van Rooyen, Dickson, Majoro, and de Wet (2010) and van Rooyen, Stewart, and de Wet (2012) conduct non-empirical synthesis of the existing literature on the impact of microfinance. Conclusions from these studies largely suggest that there is no visible impact of microfinance. For instance, with regards to female empowerment, of the four studies reviewed by van Rooyen et al. (2012), the authors indicate that three studies are inconclusive. Duvendack et al. (2011) suggest that most qualitative studies that examine microfinance’s effects on empowerment mostly present anecdotal evidence. Furthermore, it has been argued that although results from qualitative studies suggest positive effects on female empowerment, these results are often not corroborated by quantitative evidence (Armendariz & Morduch, 2010).

Given the findings from these non-empirical syntheses, it is worthwhile to examine if any new conclusions can be drawn from an empirical synthesis. However, given the scant nature of empirical studies that examine the relationships of interest, we are faced with a challenge of dealing with a small information base. This possibly brings to question policy recommendations that may arise from this study given that they rest on a somewhat weak information base. But, introducing an econometric perspective, which provides a statistical link between the existing empirical literature through the use of meta-analysis, reveals various shortcomings in the existing literature, and is of particular relevance to academics and
researchers, since it brings to light gaps in the existing literature, to enable exploration of future research avenues.

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 on female empowerment. 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 studies empirical studies on the impact of microfinance interventions on female empowerment. Based on the findings from this study, we recognize that although the evidence base of microfinance’s effect on female empowerment is quite weak, most studies focus on microcredit as a measure of microfinance, while less attention has been paid to the other dimensions of microfinance, such as micro-savings, micro-insurance and training. 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 design 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 (T. 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 impact of microfinance interventions. Thus, amidst the inconsistency regarding the effects of microfinance, we provide a reliable solution to address the heterogeneity in the existing literature.
2. Overview of Female Empowerment Measures

The fundamental measures of female empowerment are constructed mainly to capture the multidimensional nature of the status of women (Mason, 1986) with regards to key indicators such as mobility, decision making and independence, amongst other things. Hashemi, Schuler, and Riley (1996) argue that in conducting female empowerment assessments, the most challenging task is the development of a valid and reliable measurement index, given that empowerment can be considered from various perspectives.

The existing studies on the impact of microfinance on female empowerment vary significantly, not only in terms of findings made by these studies, but also in terms of the indicators and measures of female empowerment used. From the existing literature, it is apparent that there is no coherent measure of female empowerment. However, some indicators have been consistently considered as key determinants of empowerment in most studies. We focus on five of these indicators that have been used in the existing literature and are comparable across studies.

In general, some of the key indicators used include mobility, political and legal awareness, economic security (Hashemi et al., 1996; Steele, Amin, & Naved, 1998), decision making ability (Hashemi et al., 1996; Mizan, 1993; Steele et al., 1998), and increase in assets and control over these assets (Goetz & Gupta, 1996; R. Montgomery, Bhattacharya, & Hulme, 1996). In some cases, a number of these indicators are combined in the construction of measurement indices, which are believed to reflect the status of women.

We focus on studies that report on mobility, political and legal awareness, decision making power, control over finance and women’s wealth/assets. In the literature, mobility measures the ease of traveling outside the household alone. Political and legal awareness is expected to reflect a woman’s knowledge about political and legal issues. Decision making power
measures a woman’s involvement in taking non-economic and economic decisions in a household. Control over finance measures the ability to independently make purchases such as utensils, cloths, livestock and jewellery, amongst others, on behalf of the household or for personal use. The wealth/asset category is expected to capture if a woman owns properties such as agricultural land and livestock, amongst others. In the above mentioned categories, a value, usually one, is assigned to women that meet a given criteria and zero if otherwise.

3. Data

The data used in this study are empirical results retrieved from existing studies that have been included in our study. The studies included in this meta-analysis are those that examine the effects of microfinance on the female empowerment indicators mentioned earlier. We focus on four measures of microfinance, namely microcredit, access to credit, micro-savings and length of microfinance programme membership. Most observations reported in this meta-analysis are for the effects of microcredit on the various proxies of female empowerment. Two studies (Banerjee, Duflo, Glennerster, & Kinnan, 2009; H. Montgomery, 2006) use access to credit, in which cases, the independent variables captures whether or not households or individuals have access to credit or participate in microcredit programmes. Coleman (1999) and Supriya Garikipati (2008) report effects using length of time in microcredit programme as a measure of microfinance. Lastly, Ashraf, Karlan, and Yin (2010) report effects using micro-savings.

For a study to be included in this meta-analysis, it had to be an empirical study that reports effect sizes on the association between at least one of the above mentioned measures for microfinance and at least one female empowerment proxy. A few estimates from the primary studies are reported based on empowerment indices created by putting together two or more of the above mentioned empowerment indicators. However, there is no common trend which
determines how many, and which indicators should be combined to form the index. Thus, we do not report on empowerment indices.

In addition, given that partial correlation coefficients (PCCs) are used to ensure comparability of studies, studies that report only estimated coefficients, without other relevant statistics to allow for PCC calculation are excluded. Thus, overall, seven studies are included in this meta-analysis. The list of papers included in this study and the associated estimates extracted for each microfinance-empowerment association is provided in table 1.

4. Empirical Design

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 & Krueger, 1995). Meta-analysis makes it possible to combine and compare different studies, with the view of 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.

4.1. Meta-analysis tools

The methodologies adopted for this study have been used before to examine empirical research findings in economics. For instance, Mitchell, Gluch, and Bohara (2005) made use of the meta-analysis tool to examine the existing research evidence on the relationship between economic development and human rights. Likewise, Havranek and Zuzana (2010) made use of meta-analysis to examine the relationship between firm characteristics and
vertical spill-overs from FDI, and also Ugur (2013) who examined the effects of corruption on per-capita income growth.

We first calculate partial correlation coefficients (PCCs) for 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, e.g., Alptekin and Levine (2012), Ugur (2013)).

The PCC for each effect estimate is calculated as follows;

\[
 r_i = \frac{t_i}{\sqrt{t_i^2 + df_i}}
\]

(1)

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

\[
 SE_{ri} = \sqrt{\frac{1 - r_i^2}{df_i}}
\]

(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 fixed effect weighted means (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.

### 4.1.1 Fixed Effect Weighted Averages

Next, we calculate fixed effect weighted means (FEEs). FEEs are less affected by potential publication bias than the random-effects weighted averages (Henmi & Copas, 2010; T
Stanley, 2008; T. D. Stanley & Doucouliagos, 2014). Thus, we estimate FEEs and depend mainly on these for the relationship between our microfinance variables and female empowerment variables.

The FEEs are calculated using the approach used by Thomas Stanley and Doucouliagos (2007) and De Dominicis, Florax, and Groot (2008), amongst others. It is reported as follows;

\[ \bar{X}_{FEE} = \frac{\sum r_i \left( \frac{1}{SE_{ri}} \right)}{\sum \frac{1}{SE_{ri}}} \]  

(3)

Where \( \bar{X}_{FEE} \) is the fixed effect estimate weighted mean, and \( r_i \) and \( SE_{ri} \) remain as explained above. The FEEs 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.

FEEs are reported in table 1. Pitt and Khandker (1998) report on the association between microcredit and women’s assets. The fixed effect weighted mean for 30 estimates reported for this relationship is positive and statistically significant. However, drawing on inferences put across by Cohen (1988), we conclude that this effect size (0.04), although statistically significant, is of no practical relevance. According to Cohen (1988) an effect size represents a large effect if its absolute value is greater than 0.4, medium effect if it is 0.1 \( \leq x < 0.4 \) and small effect if it is less than 0.1. Still related to women’s assets, we find no evidence of an association between the length of credit programme membership and women’s wealth. This conclusion is drawn based on evidence from four estimates presented by Coleman (1999).

[INSERT TABLE 1 HERE]
Li, Gan, and Hu (2011) and Alam (2012) both report on the effects of microcredit on awareness. Of the 22 reported estimates on this relationship, 16 estimates present a positive and statistically significant weighted average of 0.10. Thus, based on the reported evidence, there is a weak positive association between microcredit and awareness. Similarly, evidence suggests a positive association between microcredit and control over finance. This is however a medium effects and is mainly drawn from 24 estimates extracted from Li et al. (2011). On the contrary, based on two estimates extracted from Supriya Garikipati (2008), we find no significant association between the length of credit programme membership and control over finance.

Two estimates presented by Supriya Garikipati (2008) are associated with an insignificant weighted average. With regards to microcredit and decision making, we report 34 estimates extracted from three primary studies (Alam, 2012; Supriya Garikipati, 2008; Li et al., 2011). Of the 34 estimates, 27 from one study (Li et al., 2011) is positive and statistically significant with a medium effect size of 0.13. Further, based on 20 estimates reported by Ashraf et al. (2010) on the effect of micro-savings on decision making, we estimate a significant weighted average of 0.07, which represents a weak positive association between these two variables. In contrast, two estimates drawn from Banerjee et al. (2009), which report on the association between access to credit and decision making present a statistically insignificant average. Lastly, a total of nine estimates drawn from two studies (Alam, 2012; Li et al., 2011) present no significant association between microcredit and mobility.

Consequently, the weighted averages presented for the associations between microfinance measures and female empowerment measures, mainly point to either an insignificant association or a weak/medium positive association.
4.1.2. Precision Effect and Funnel Asymmetry Tests (PET/FAT)

We further investigate the robustness of the FEEs to potential threats of publication selection bias. To explore issues of publication bias thoroughly, we conduct a formal test - the precision effect and funnel asymmetry tests (Egger, Smith, Schneider, & Minder, 1997; T Stanley, 2008). Conducting this analysis 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 effect’ beyond bias. A commonly used alternative is the funnel plot, which helps to visually inspect bias. However, funnel plots are only useful for visual inspection of publication selection bias and cannot be precise in determining the magnitude and significance of bias. Thus, for brevity, we circumvent the use of funnel plots and resort to the use of the more formal and thorough PET/FAT analysis. The PET/FAT analysis involves the estimation of a bivariate weighted least square (WLS) model.

\[ t_i = \alpha_0 + \beta_0 \left( \frac{1}{SE_{ri}} \right) + \varepsilon_i \]  \hspace{1cm} (4)

Where \( t_i \) is the t-value reported by primary studies. \( \beta_0 \) and \( \alpha_0 \) represent the constant term and the slope coefficient, respectively. While, \( SE_{ri} \) is the standard error of the estimate and \( 1/SE_{ri} \) is the precision. Thus, the coefficient of the precision \( (1/SE_{ri}) \) is the measure of genuine effect given that it is statistically significant. The funnel asymmetry test (FAT) involves testing for \( \alpha_0 = 0 \) and the precision effect test (PET) tests for \( \beta_0 = 0 \). If the null hypothesis is rejected in the FAT, this means that asymmetry exists, in which case, the sign of the coefficient of \( \alpha_0 \) determines the direction of bias.

T 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. Equation 5 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.

$$ t_i = \beta_0 \left( \frac{1}{SE_{ri}} \right) + \alpha_0 (SE_{ri}) + v_i \quad (5) $$

Given the small number of studies and estimates this meta-analysis draws its inference from, we are not able to conduct PET/FAT analysis for some hypothesised relationships. Results for associations that have enough observations for a PET/FAT analysis are presented in table 2. We find no significant associations between microcredit and the outcome variables awareness, decision making power and mobility. This is somewhat consistent with fixed effect weighted averages, especially in the case of microcredit’s association with mobility, and also with awareness, where the estimated average reflects no practical significance.

[INSERT TABLE 2 HERE]

4.1.3. Multivariate Meta-regression Analysis (MRA)

The use of the PET/FAT analysis makes it possible to make precise inferences regarding the existence of genuine effects and publication bias. 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 do not include moderating variables. Based on this understanding, we also conduct a multivariate meta-regression (MRA), which takes into account various moderating variables.
Given that we have only a few studies but with several estimates, we account for this multi-level structure and its implied dependence. A conventional MRA model has two error terms given that PCCs \( (r_i) \) have a normal distribution around the their mean values and this distribution is subject to disturbances from two sources - within-study variance and between-study variance (Harbord & Higgins, 2008). We make one of the error terms a study-level fixed-effect to account for the multi-level structure and its implied dependence (T Stanley & Doucouliagos, 2012). Thus, the MRA model used is specified as follows:

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

(6)

Here, all variables remain as explained before and subscript \( j \) represents study \( j \) from which observation \( i \) is extracted. \( \epsilon_j \) is the study-specific fixed effect and \( u_{ji} \) is the independent and identically distributed error term. \( Z_{ki} \) is a vector of binary variables that account for variations in the primary studies.

Ideally, well-designed meta-regressions account for study-level variables such as study designs, cultural variations, publication type and data period, amongst other things, that reflect variations in the literature in order to control for heterogeneity. However, given the earlier mentioned data constraints, we are only able to control for data period and cultural variations.

We ran an MRA for all studies that use microcredit as a measure of microfinance. Given that each outcome variables is considered a measure of female empowerment, we pool together estimates that explain the effects of microcredit on all our empowerment measures and control for awareness, women wealth, control over finance and decision making power. We also find that most studies reporting microcredit’s effects of female empowerment consider case studies in Southeast Asia (Alam, 2012; Supriya Garikipati, 2008; Pitt & Khandker,
1998). Thus, in the MRA, we control for studies conducted with Southeast Asia as a case study to see if this demography affects the effect of microcredit on female empowerment.

Furthermore, we control for data period to examine the nature of reported estimates, given that over time studies emerge with newer datasets. We note that majority of estimates reported in this meta-analysis are drawn from studies that use data covering at least the year 2000. Thus, we use the year 2000 as the reference point and introduce a dummy for studies that report estimates using data collected at least from the year 2000.

We estimate MRA equation 6 with heteroskedasticy robust and cluster (by study) robust estimates using the discussed moderating variables. The cluster-robust standard error estimations are taken as the preferred model given that they take account of dependence between the multiple estimates reported by the same or different studies. The results from the MRA are presented in table 3.

[INSERT TABLE 3 HERE]

The coefficient of precision is statistically insignificant. Hence, it can be said that, after controlling for moderating variables, the overall effects of microcredit on female empowerment is insignificant. However, the results from the MRA indicate that some moderating variables have significant effects on the reported effect-size estimates from the primary studies. Thus, microcredit’s marginal effect on female empowerment is conditional on the moderating variables and can be calculated as the sum of all significant coefficients – except the intercept term which captures residual selection bias. Hence, given that the modelled characteristics hold, the marginal effect of microcredit on female empowerment is $0.0813 (=0.0954 + 0.1049 + 0.0321 - 0.1511)$. Based on Cohen’s guidelines, this represents a weak effect and thus we can conclude that there’s no meaningful effect of microcredit on female empowerment.
In addition, we find that the moderating variables included in our MRA account for only 9.38% of variations $t$-values. We find positive and significant effects for dummies representing awareness, control over finance and decision making. These coefficients are mostly small and thus reflect the weak effect of microcredit that was reported for these variables.

5. Relation to Literature

As shown earlier from the weighted average results, 16 estimates reporting effects on awareness (72.73% of total estimates) present a significant but weak positive weighted average. This suggests the possibility of microcredit’s effectiveness on improving the political and legal awareness of women. This is likely considering that women in self-help groups usually develop greater social networks while improving access levels to economic and financial resources. Establishing these social networks makes it possible for women to learn from one another. This also increases the level of awareness as well as political and social inclusion among women (Bali Swain & Wallentin, 2012; Beteta, 2006; Dijkstra, 2002).

With regards to microcredit’s effect on control over finance and decision making, results suggest medium positive effects. With the support from MFIs (which includes microcredit and training) women are able to take better control over their financial assets including their savings and income (Li et al., 2011). This, in the long-run, affects their participation in household decision making (Hashemi et al., 1996; Mizan, 1993; Pitt et al., 2006). Most MFIs aim to assist women achieve financial independence. Thus, women are said to have become empowered economically when they begin to take control over their financial assets (Li et al., 2011). Economic empowerment underpins other dimensions of empowerment (Ashraf et al., 2010; Mayoux, 1998, 2001). As Goetz and Gupta (1996) and Anderson and Eswaran (2009) emphasise, with economic empowerment, there is an augmentation in the autonomy of
women, which is usually evidenced in decisions made in terms of purchases. Furthermore, Armendariz and Morduch (2010) argue that microfinance affects the bargaining power of women by influencing the level of resources they have.

It is however observed that, with the exception of insignificant averages, the effect sizes explaining the association between microcredit and the various empowerment measures, although positive are quite small. This, amongst other things, suggests that some other factors may be in play that hinder microfinance’s effect on female empowerment. One of such factors could be interference from spouses. In some communities, women receive microloans and end up giving them to their spouses who fail to use them productively (Supriya Garikipati, 2012; Rahman, Junankar, & Mallik, 2009). Furthermore, microcredit programmes that exclude men may end up exacerbating discrimination against women and reinforcing gender inequality (R. Montgomery et al., 1996) The exclusion of men from microcredit programmes makes them less supportive to their spouses as they feel that, in time, they would be displaced as the primary ‘breadwinners’ of the household (Armendariz & Morduch, 2010; Mayoux, 1999).

In addition, the presence of social and cultural constraints in some communities, which are imposed on women, impede the process of female empowerment (Bali Swain & Wallentin, 2012). In this regard, although microfinance positively affects female autonomy as well as accumulation of resources, this does not necessarily empower them as there are various dimensions to empowerment. Some of which are hindered by the presence of social and cultural constraints.

Furthermore, as discussed by Supriya Garikipati (2008), it is likely women are more concerned about the improvement of their household rather than their individual wellbeing and status in the family. Evidence suggests that lending to women strengthens the household
as a whole by improving the household’s ability to cope with various vulnerabilities. However, the women themselves do not experience significant changes in their status. This suggests that women are more concerned about the wellbeing of their homes and families. As a result, they usually make purchases and invest in items that would benefit the entire family, rather than themselves individually.

6. Summary and Conclusions

Using meta-analysis, we synthesize the existing evidence of the impact of microfinance interventions on five measures of female empowerment. Four measures of microfinance are reported - microcredit, access to credit, micro-saving and length of microcredit programme membership. However, majority of the estimates reported are for microcredit’s effect. We adopt three major meta-analysis tools – 1) The fixed effect weighted means of individual studies, 2) Bivariate WLS precision effect and funnel asymmetry tests (PET/FAT) and 3) Multivariate WLS meta-regression analysis (MRA).

Overall, the results indicate that credit access and length of involvement in microcredit programme have no significant associations with female empowerment indicators. For microcredit and micro-savings, we mostly find a weak positive association with empowerment indicators. This suggests that although effect sizes are statistically significant, they present no meaningful positive effect.

The findings from this study present some relevant recommendations for future research. First, this study reveals that the empirical literature on the impact of microfinance on female empowerment is lacking. Thus, there is the need for more research to be conducted in this area, particularly, using a wider range of metrics for microfinance rather than microcredit, as microcredit alone does not reflect microfinance in entirety. In addition, it is in the best interest of future research that besides the individual indicators of female empowerment, a
general consensus should be reached on a universally accepted index for female empowerment. This, amongst other things, allows for the ease in comparing results from different studies, and a stronger base for both empirical and non-empirical synthesis. Duvendack et al. (2011) suggest that few quantitative studies exist on the impact of microfinance on female empowerment because of unresolved issues of measuring female empowerment. Thus, if much attention is devoted to the construction of reliable female empowerment measures, this can go a long way to increase the number of studies, and promote the reliability, of studies that examine microfinance’s effect on female empowerment.

As it stands, there is no substantive evidence to suggest that microfinance has a positive impact on female empowerment. This brings into question the viability of microfinance as an empowerment tool. Of course, a major limitation faced by this study was the lack of a strong information base and thus policy makers would have to put some level of precedence on the design of more robust studies that examine effects on empowerment. Even so, with the existing trends, based on inferences drawn from recent systematic reviews and this current study, it might be worthwhile for policy makers to reconsider the viability of microfinance as a development tool, and where necessary, consider possible alterantiveness.

7. References


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

<table>
<thead>
<tr>
<th>Paper</th>
<th>No. of Estimates</th>
<th>Simple Mean</th>
<th>Weighted Mean (FE)</th>
<th>Significance</th>
<th>Confidence Interval</th>
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</tr>
<tr>
<td>Ashraf et al. (2010)</td>
<td>20</td>
<td>0.0744</td>
<td>0.0659</td>
<td>Yes</td>
<td>(0.0429, 0.0889)</td>
</tr>
<tr>
<td>Micro-savings and Decision Making</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Banerjee et al. (2009)</td>
<td>2</td>
<td>-0.0004</td>
<td>-0.0004</td>
<td>No</td>
<td>(-0.0066, 0.0058)</td>
</tr>
<tr>
<td>Credit Access and Decision Making</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Coleman (1999)</td>
<td>4</td>
<td>0.0401</td>
<td>0.0404</td>
<td>No</td>
<td>(-0.0217, 0.1024)</td>
</tr>
<tr>
<td>Member Length and Women Wealth</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Supriya Garikipati (2008)</td>
<td>2</td>
<td>-0.1567</td>
<td>-0.1577</td>
<td>No</td>
<td>(-0.3541, 0.0388)</td>
</tr>
<tr>
<td>Member Length and Finance Control</td>
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</tbody>
</table>

### Table 2 PET/FAT Results with $t$ values as dependent variable

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) Awareness</th>
<th>(3) Decision Making</th>
<th>(4) Mobility</th>
</tr>
</thead>
<tbody>
<tr>
<td>Precision ($\beta_0$)</td>
<td>-0.0162</td>
<td>0.0020</td>
<td>-0.0064</td>
</tr>
<tr>
<td>Bias ($\alpha_0$)</td>
<td>1.1247***</td>
<td>1.1707***</td>
<td>1.3199</td>
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<tr>
<td></td>
<td>(0.0095)</td>
<td>(0.0140)</td>
<td>(0.0240)</td>
</tr>
<tr>
<td></td>
<td>(0.2760)</td>
<td>(0.3367)</td>
<td>(0.7654)</td>
</tr>
<tr>
<td>Observations</td>
<td>22</td>
<td>34</td>
<td>9</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.1268</td>
<td>0.0006</td>
<td>0.0100</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Precision</td>
<td>0.2331</td>
<td>0.2331</td>
</tr>
<tr>
<td></td>
<td>(1.6387)</td>
<td>(0.7013)</td>
</tr>
<tr>
<td>Awareness</td>
<td>0.0954***</td>
<td>0.0954***</td>
</tr>
<tr>
<td></td>
<td>(0.0120)</td>
<td>(0.0236)</td>
</tr>
<tr>
<td>Wealth</td>
<td>0.0384</td>
<td>0.0384</td>
</tr>
<tr>
<td></td>
<td>(0.0914)</td>
<td>(0.0389)</td>
</tr>
<tr>
<td>Control over Finance</td>
<td>0.1049***</td>
<td>0.1049</td>
</tr>
<tr>
<td></td>
<td>(0.0011)</td>
<td>(0.0136)</td>
</tr>
<tr>
<td>Decision Making</td>
<td>0.0321***</td>
<td>0.0321</td>
</tr>
<tr>
<td></td>
<td>(0.0018)</td>
<td>(0.0288)</td>
</tr>
<tr>
<td>Data Period Dummy</td>
<td>-0.0516</td>
<td>-0.0516</td>
</tr>
<tr>
<td></td>
<td>(1.3019)</td>
<td>(0.5556)</td>
</tr>
<tr>
<td>Southeast Asia Dummy</td>
<td>-0.1511**</td>
<td>-0.1511***</td>
</tr>
<tr>
<td></td>
<td>(0.0450)</td>
<td>(0.0345)</td>
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<tr>
<td>Constant</td>
<td>-1.1371</td>
<td>-1.1371</td>
</tr>
<tr>
<td></td>
<td>(15.6102)</td>
<td>(6.6531)</td>
</tr>
<tr>
<td>Observations</td>
<td>121</td>
<td>121</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.0938</td>
<td>0.0938</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses

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

(1) - Cluster robust standard errors
(2) - Heteroskedasticity robust standard errors