IZA DP No. 10046

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July 2016

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Discussion Paper No. 10046
July 2016

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July 2016

ABSTRACT

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This paper examines the impact of micro-credit on employment. Household-level data was collected, following a quasi-experimental design, in Bangladesh and Pakistan. Three borrower groups are compared: Current borrowers; Pipeline borrowers and Non-borrowers. Pipeline borrowers are included to control for self-selection effects. It is argued that micro-credit causes a substitution of employment away from employment-for-pay to self-employment. Therefore, the effect on total employment is ambiguous. OLS and fixed effects regression are used to examine separately self-employment and employment-for-pay between three groups of borrowers. For Pakistan, there is no evidence that micro-credit effects employment. However, for Bangladesh, there is robust evidence consistent with this hypothesis.

JEL Classification: G21, J22, I39

Keywords: micro-credit, poverty, self-employment

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The Impact of Micro-credit on Employment: Evidence from Bangladesh and Pakistan

1. Introduction

There is considerable interest in the impact of micro-credit on poverty in low-income countries. There is a growing belief amongst politicians and policy-makers that micro-credit is a major poverty-reduction tool in such countries. However, despite the increasing popularity of micro-credit, the results of empirical studies of its poverty-reducing impacts are at best mixed. For example, Duvendack et al. (2011, p. 4), after a thorough review of a large number of empirical studies, conclude: "… almost all impact evaluations of microfinance suffer from weak methodologies and inadequate data… thus the reliability of impact estimates are adversely affected. This can lead to misconceptions about the actual effects of a microfinance programme". Since more money for micro-credit, means less money for other poverty-reducing interventions, it is critical to establish whether it does result in a sustained reduction in poverty.

There are various mechanisms by which micro-credit can impact on poverty. One argument is that micro-credit increases employment. More specifically, micro-credit loans are used to purchase capital, and once this capital in combined with available labour, there is an increase in employment. Since employment is perhaps the best predictor of poverty, any policy that increases employment, is potentially important in term of poverty reduction. However, we believe this view is a serious over-simplification. It is our view that in order to understand this relationship it is necessary to distinguish between the types of work being carried out. The key distinction for us is between "employment-for-pay" and "self-employment". Our hypothesis is that micro-credit increases self-employment but decreases employment-for-pay. That is, micro-credit leads to a substitution away from employment-for-pay to self-employment, with the overall impact on "total" employment being ambiguous. It follows that if earnings from self-employment are sufficiently above those for employment-for-pay, then the employment impact of micro-credit could lead to lower poverty, even with no increase in overall employment. If this is the case, then it is not surprising that empirical studies that have not distinguished between these types of employment have very mixed results (see for example, Al-Mamun, Wahab and Malarvizhi, 2011; Angelucci, Karlan and Zinman, 2015; Attanasio et al., 2015; Augsburg et al., 2015; Garnani, 2007; Karlan and Zinman, 2011; Lensink and Pham, 2011; Khan, 1999; Khandker, Samad and Khan, 1998; McKernan, 2002; Panjaitan-Drioadisuryo and Gould, 1999; and Pitt, 2000).

In order to explore this hypothesis empirically, this paper examines the relationship between micro-credit and employment at the household-level in Bangladesh and Pakistan with micro-level data collected following a quasi-experimental design. The remainder of the paper is organised as follows. Section 2 presents the methodology and data. OLS and fixed effects regression are used to examine separately self-employment and employment-for-pay between three groups of borrowers. The estimates are given in Section 3. In Pakistan there is little evidence consistent with the view that micro-credit causes a substitution away from employment-for-pay to self-employment. However, in Bangladesh, there is robust evidence consistent with this hypothesis. Concluding Comments follow in Section 4.

2. Methodology

The statistical analysis presented in this section uses survey data collected in Bangladesh and Pakistan based on a “quasi-experimental” design (see Dinardo, 2008; Meyer, 1995; Todd, 2008). The design consists of three groups of households: (1) Current Borrowers; (2) Non-borrowers and (3) Pipeline borrowers. “Current Borrowers” are households that at time of interview, were in receipt of a micro-credit loan. “Non-borrowers” are households that have never applied for a micro-credit loan and consequently are not in receipt of a loan at the time of interview. Since these non-borrowers have never had a micro-credit loan, then there can be no effect of micro-credit. If current borrowers are not a "self-selected" group, then a comparison of current borrowers with non-borrowers would form the basis of a meaningful comparison of the impact of micro-credit on employment.

There is however considerable concern that self-selection is a problem in the evaluation of micro-credit. Households that apply for a micro-credit loan may be very different in terms of both observable and non-observable characteristics that underpin the decision to apply for a loan (see Tedeschi, 2007). Put differently, it is unlikely that borrowers are a random subset of all potential borrowers. It is possible to control statistically for certain observable characteristics through (for example) multiple-regression. However, non-observable characteristics are unmeasured, and therefore cannot be controlled for in the same way. It is possible to control for self-selection by comparing current borrowers and non-borrowers to so-called "Pipeline borrowers". Pipeline borrowers are households that have successfully applied for a micro-credit loan but at the time of interview had not received the money. Since they have applied for a loan they are similar to current borrowers in unobserved characteristics. Put differently, it is difficult to imagine why they would be different in unobserved characteristics (especially after controlling for observed differences). Pipeline borrowers have never held a micro-credit loan and have not yet received the money for what will become their current loan. Therefore, for this group of borrowers there can be no micro-credit effects caused by spending/investing since they do not have the money in hand to do so (see Coleman, 1999 2006; Chowdhury, Ghosh and Wright; 2005, Karlan, 2001; Khan and Wright, 2015).

A comparison of current borrowers, pipeline borrowers and non-borrowers can be used to more convincingly estimate the impact of micro-credit on employment. Any difference between non-borrowers and pipeline borrowers can be attributed to self-selection (and not to micro-credit), while any difference between current borrowers and pipeline borrowers can be attributed to micro-credit. However, this assumes that other factors that impact on employment are "held constant", since micro-credit is not the only possible factor affecting employment. Multiple regression can be used to control for measured factors, such as age, education and household size. In addition, it is likely the case that geographic location has an effect on employment. More specifically, in countries such as Bangladesh and Pakistan, there is considerable geographic variation is the quantity and quality of arable land. Given agriculture is the main form of employment in both of these countries, it is not difficult to believe that arable land is a key determinant of employment patterns. It is difficult to measure this variability directly. However, fixed effects can be used to proxy this potentially important geographical variation. If micro-credit does have an impact on employment, you would expect such effects to be largely unaffected by the inclusion of geographically-defined fixed effects. Further details of the statistical model are discussed below.

2.1. Data

The data for Pakistan was collected in the period December, 2008 to February, 2009. Face-to-face interviewing was used. The sampling frame used to draw the sample of current borrowers and pipeline borrower is based on three microcredit lending institutions: (1) *Khushhali Bank Limited*; (2) *National and Rural Support Programme*; and (3) *Akhuwat*. The authors believe that these three institutions represent well the micro-credit sector in Pakistan. The total sample size is 468 households (see Table 1).This is the same data used in Khan and Wright (2015), and we refer the reader to this study for further detail.

The data for Bangladesh was collected in the period June. 2014 to September, 2014. Face-to-face interviewing was used. The sampling frame was provided by the *Association for Social Advancement*, more commonly known as "ASA". Established in 1978, ASA is the world's largest microcredit institution. In terms of total loans, it is only second to the Grameen

Bank in Bangladesh. With nearly 3,000 branches, the authors believe that the scale of ASA's micro-credit activities makes it representatives of the sector as a whole. The total sample size is 1,522 households (see Table 1). This is the same data used by Rahman (2016).

2.2. Statistical Model

The statistical model is of the form:

$$ln(Emp)_{ij} = \alpha_0 + \alpha_1 Current_{ij} + \alpha_2 Pipeline_{ij} + \alpha_3 ln(Age_{ij}) + \alpha_4 ln(School_{ij}) + \alpha_5 ln(nChildF_{ij}) + \alpha_6 ln(nChildM_{ij}) + \alpha_7 ln(nAdultF_{ij}) + \alpha_8 ln(nAdultM_{ij}) + \alpha_9 ln(nOlderF_{ij}) + \alpha_{10} ln(nOlderM_{ij}) + \theta_j + \mu_i$$

where "*Emp*" is the number of individuals in household "*i*" in region "*j*" who are employed. "*Current*" is a dummy variable coded "1" if the household is a current borrower and coded "0" if not. "*Pipeline*" is a dummy variable coded "1" if the household is a pipeline borrowers and coded "0" if not. The excluded category is non-borrower. "*Age*" is the age of the household head. "*Schoo*l" is the number of years of education of the household head. "*nChildF*" and "*nChildM*" are the number of female and male children in the household. "*nAdultM*" and "*nAdultF*" are the number of female and male adults (less than age 65) on the household."*nOlderM*" and "*nOlderF*" are the number of email and male elderly adults (age 65 and older) in the household. "θ" is a regional-level fixed effect (discussed below) and "μ" is a random error term. Since all the variables are expressed in natural logarithms (except "*Current*" and "*Pipeline*"), the parameters can be interpreted as elasticities.

The inclusion of "*Age*" and "*School*" are intended to capture differences in the head of the household. Since household heads are traditionally the main decision-makers in low-income households in both Bangladesh and Pakistan, age and schooling is intended to proxy socioeconomic differences that may affect decisions relating to the employment of household members. The sex-specific number of children, number of adults and number of elderly adults is intended to represent the number of potential workers in the households. These variables sum to total household size. Holding other factors constant, you would expect larger households to have a larger number of household members employed.

θ_j are regional-level fixed effects. Fixed effects control for persistent differences across regions that impact on employment. In Pakistan, the fixed effects are based on 30 "Union Council" areas. A union council is an elected local government for a small group of villages in close geographical proximity. In Bangladesh, the fixed effects are based on 54 "Thana" areas. Traditionally a Thana was an area controlled by a police station. If micro-credit does have an impact on employment, then you would expect to find a similar set of parameters for key variables in regression models with and without fixed effects. That is, the estimates are robust to the inclusion of variables that capture persistent differences across regions. If the opposite is the case, then one possible conclusions is that it is regional differences—and not micro-credit—that is important in explaining differences in employment across households. In other words, if micro-credit is a true determinant of differences in employment across households, you would not expect the inclusion of geographically-defined fixed effect to have impact on the estimates.

The numbers employed in the household, "*Emp*", is measured in three ways. The first is the total number of household members employed, consisting of both those employed-for-pay and those self-employed. The second is only the number of household members employed-for-pay. The third is the number of household members who are self-employed. Estimating regression models separately for these three measures of household employment will provide information about the impact of micro-credit on the two main types of employment.

Remembering that the excluded category is "Non-borrowers", the marginal difference in percentage terms of being a current borrower relative to a non-borrower is:

$$A = Effect(CB{:}NB) = [\exp(\alpha_1)-1] \times 100.$$

In turn, the marginal effect of being a pipeline borrower relative to a non-borrower is:

$$B = Effect(PB{:}NB) = [\exp(\alpha_2)-1] \times 100.$$

As discussed above, the latter difference can be attributed to self-selection effects and not to micro-credit. Therefore the effect of micro-credit on employment, purged of self-selection effects, is the difference between current borrowers effect and pipeline borrowers:

$$Difference = A - B = Effect(CB{:}NB) - Effect(PB{:}NB).$$

3. Results

Table 1 reports the means and standard deviations for the three employment variables broken down by borrower groups. The upper panel of the table is for Pakistan while the lower panel is for Bangladesh. Also shown in this table is an F-test that provides a statistical test of the differences across the three borrower groups. It is interesting to note that for both countries the F-test suggests that there is no statistically significant difference across the groups when those employed-for-pay and those self-employed are lumped together (denoted "Both" in the table).

<<<< Table 1 About Here >>>>

The situation is, however, quite different when the two types of employment are considered separately. In Pakistan, the number of self-employed is higher for current borrowers and pipeline borrowers than for non-borrowers, and this difference is statistically significant at below the 1% level. Likewise, the number of employed-for-pay is lower for current borrowers and pipeline borrowers than for non-borrowers, although this difference is only statistically significant at the 10% level. A similar pattern is observed for Bangladesh. For both countries, it appears that self-employment compared to employment-for-pay is higher for current borrowers compared to non-borrowers. However, the same is the case for pipeline borrowers compared to non-borrowers. This finding is suggestive of self-selection given that pipe-line borrowers have not received the loan and the money is not yet available to enhance self-employment. It is likely that households that apply for micro-credit loans have above average levels of self-employment and below average level of employment-for-pay prior to applying.

The across borrower groups differences shown in Table 1 do not control for other factors that potentially impact on employment. Table 2 reports the means and standard deviations for the control variables included in the regression models. The table also reports F-test that tests for difference in these variables across the three borrower groups. It is clear from this table that there are differences across these groups but that the pattern is not consistent between the two countries. For example, in Pakistan the level of schooling of household heads is much higher for current borrowers compared to non-borrowers. However, it is even higher for pipe-line borrowers. In Bangladesh, the opposite is observed—the level of schooling of household heads is lower for current borrowers compared to non-borrowers. Like in Pakistan, the level of school of household heads is highest for pipeline borrowers. There are also a significant differences in the age of household heads in Pakistan across the groups but this is not the case in Bangladesh. There are also differences in the age and sex mix of household of members but the pattern is not the same between the two countries. This suggests that the differences in the control variables across the three groups summarised in Table 2 does not provide a "neat" explanation of the differences in the employment variables summarised in Table 1.

<<<< Table 2 About Here >>>>

Table 3 reports the estimates of the regression models where the dependent variable is the total number of household members employed (i.e. numbers employed-for-pay and numbers self-employed added together). Columns (1) and (2) are OLS estimates and Columns (3) and (4) are fixed effect estimates. Turning first to the OLS estimates, in both countries, the pipeline borrowers dummy is not statistically significant. However, the current borrower variables is statistically significant, at the 5% level in Pakistan and at the 10% level in Bangladesh, with a positive sign. This suggests that total employment is higher for current borrowers compared to non-borrower households. In addition, there is no difference in total employment between pipeline borrowers and non-borrowers. The point estimates indicate that total employment is about 10.6% higher in Pakistan, and 6.4% higher in Bangladesh, compared to non-borrowers. However, when fixed effects are added, this difference disappears for Pakistan [see Column (3)], suggesting that there are no statistically significant difference across the three borrower groups. However, for Bangladesh when fixed effect are added, the difference remains statistically significant, with total employment being higher for current borrowers compared to pipeline borrowers and non-borrowers [see Column (4)].

<<<< Table 3 About Here >>>>

The estimates in Table 3 suggest a positive relationship between the age of the household head and numbers employed. However, this relationship is only statically significant in Bangladesh. Somewhat surprisingly, there is a negative relationship between the schooling of the household head and number employed. Again this relationship is only statistically significant in Bangladesh. It is important to note that in both countries there is a positive relationship between the number of both female and male “adult” household members and numbers employed. The same is the case for “older” male household members but not for “older” female household members. However, the estimates are quite mixed for the number of female and male children in the household. One must be careful with the interpretation of these child variables as they potentially capture information about the prevalence of child labour (as is discussed in more details below).

Table 4 reports the estimates of the regression models where the dependent variable is the total number of household members who are employed-for pay. The layout is the same as Table 3. These estimates are best viewed relative to the estimates of the regression models where the dependent variable is the total number of household members who are self-employed. These estimates are shown in Table 5. It is not an exaggeration to conclude that the borrower group variables in Table 4 are the "mirror image" of the estimates in Table 5. More specifically, the OLS estimates shown in Table 4 [Columns (1) and (2)] suggest that in both countries the numbers employed-for-pay is lower for current borrowers compared to non-borrowers. However, the OLS estimates shown in Table 5 suggest that in both countries the numbers self-employed is higher for current borrowers compared to non-borrowers.

<<<< Tables 4 and 5 About Here >>>>

Focussing on the OLS estimates only, one could conclude that micro-credit exerts a positive impact on self-employment and a negative impact on employment-for-pay. These estimates are also indicative of micro-credit being associated with a substitution away from employment-for-pay to self-employment. However, for Pakistan when fixed effects are added none of the borrower group variables are statistically significant. However, this is not the case for Bangladesh. When fixed effects are added, employment-for-pay is lower and self-employment is higher for current borrowers compared to non-borrowers. In addition, for Bangladesh the estimates for pipe-line borrower suggest that there is little difference in the numbers employed-for-pay and numbers self-employed between pipeline borrowers and non-borrowers.

Table 6 gives the marginal effects for each of the borrower groups based the regression estimates given in Tables (3), (4) and (5). As discussed above, the difference in the marginal effects between pipeline borrowers and non-borrowers can be interpreted as a selection effect, and as a consequence cannot be attributed to micro-credit. On the other hand, the difference in the marginal effects between current borrowers and pipeline borrowers is purged of selection effects, and as a consequence can be interpreted as micro-credit effect. Therefore, this key estimate in Table 6 is shown in the rows labelled “Difference”.

<<<< Table 6 About Here >>>>

Turning first to Panel (A) in Table 6, the main finding is that the estimates of the impact of micro-credit on total employment are small. For Pakistan, the “Difference” estimates based on OLS regression is 3.7% and slightly higher at 6.3% based on fixed effects regression. For Bangladesh, the “Difference” estimates are not too different from those for Pakistan: 5.7% based on OLS regression and 5.6% based on fixed effects regression. It is interesting to note that most of the difference in numbers employed between current borrowers and non-borrowers in Pakistan can be attributed to selection effects and not to micro-credit. The marginal effect for current borrowers/non-borrowers is 10.6% based on OLS regression and 27.6% based on fixed effects regression. The marginal effect for pipeline borrowers/non-borrowers is 6.9% based on OLS regression and 21.3% based on fixed effects regression. Based on OLS regression, about 65% of the difference between current borrowers is due to selection effects (i.e. 6.9%/10.6% is a difference of 65.1%). Based on fixed effects regression, the difference is nearly 80% (i.e. 21.3%/27.6% is a difference of 77.2%).

On the other hand, in Bangladesh most of the difference in numbers employed between current borrowers and non-borrowers cannot be attributed to selection effects. The marginal effect for current borrowers/non-borrowers is 6.4% based on OLS regression and 6.5% based on fixed effects regression. The marginal effect for pipeline borrowers/non-borrowers is 0.7% based on OLS regression and 0.9% based on fixed effects regression. Based on OLS regression, about 10%of the difference between current borrowers is due to selection effects (i.e. 0.7%/6.4% is a difference of 10.9%). Based on fixed effects regression, the difference is nearer 15% (i.e. 0.9%/6.5% is a difference of 13.8%). It is important to note that the results are robust to the regression method used—the estimates are very similar for both OLS and fixed effects regression. Given this robustness, coupled with the small selection effects, there is a stronger case to attribute the difference in total number employed between current borrowers and non-borrowers to micro-credit in Bangladesh.

Panel (B) of Table 6 gives the marginal effects based on the regression models where the dependent variable is the numbers employed-for-pay. Turning first to the estimates for Pakistan, there is little evidence that micro-credit impacts on the numbers employed-for-pay. The marginal effect for current borrowers/non-borrowers is -14.5% based on OLS regression and -16.4% based on fixed effects regression. That is, the numbers employed-for-pay is lower for current borrowers and for non-borrowers. However, the marginal effect for pipeline borrowers/non-borrowers is -19.1% based on OLS regression and -22.7% based on fixed effects regression. In other words, the marginal effect for pipeline borrowers/non-borrowers is larger in absolute value than the marginal effect for pipe-line borrowers. This results in a "Difference" estimate of +4.6% based on OLS regression and +6.4% based on fixed effects regression. Again this supports the finding that most of the difference in employment between current borrowers and non-borrowers is due to selection effects.

The marginal effects shown for Bangladesh in Table 6 for employed-for-pay [Panel (B)] suggest that the numbers employed-for-pay is lower for current-borrowers compared to non-borrowers. The marginal effect for current borrowers/non-borrowers is -13.8% based on OLS regression and -13.3% based on fixed effects regression. That is, the numbers employed-for-pay is lower for current borrowers and for non-borrowers. However, the marginal effect for pipeline borrowers/non-borrowers is -5.7% based on OLS regression and -6.1% based on fixed effects regression. This results in a "Difference" estimate of -8.1% based on OLS regression and -7.2% based on fixed effects regression. The OLS estimates suggests that around 40% of difference in the numbers employed-for pay between current borrows and non-borrowers can be attributed to selection effects (i.e. the difference -5.7%/-13.8% as a percentage is 41.3%) and around 60% can be attributed to micro-credit (i.e. the difference -8.1%/-13.8% as a percentage is 58.7%). The fixed effects estimates suggests that around 45% of difference in the numbers employed-for pay between current borrowers and non-borrowers can be attributed to selection effects (i.e. the difference -6.1%/-13.3% as a percentage is 45.9%) and around 55% can be attributed to micro-credit (i.e. the difference -87.2%/-13.3% as a percentage is 54.1%). Unlike what was found for Pakistan, around half the difference between current borrowers and non-borrowers can be attributed to selection effects while the other half can be attributed to micro-credit.

Panel (C) of Table 6 shows the marginal effects based on the regression models where the dependent variable is the numbers self-employed. For both countries, the marginal effects for current borrowers/non-borrowers is positive and quite large in magnitude. Turning first to the estimates for Pakistan, the marginal effect for current borrowers/non-borrowers is 28.3% based on OLS regression and 33.4% based on fixed effects regression. Again it is the case that most of this difference can be attributed to selection effects. In fact, the marginal effects for pipeline borrowers/non-borrowers are large. More specifically, 31.1% is based on OLS regression and 34.4% is based on fixed effects regression. Given these large magnitudes, it is not surprising to find that the "Difference" estimates are negative and very small in magnitude. This suggests that most, if not all, of the difference in the numbers of self-employed between current borrowers and non-borrowers is due to selection effects.

The situation is quite different for Bangladesh. The marginal effect for current borrowers/non-borrowers is 23.4% based on OLS regression and 22.6% based on fixed effects regression. The marginal effects for pipeline borrowers/non-borrowers are sizeable. More specifically, 5.8% based on OLS regression and 7.6% based on fixed effects regression. This generates a "Difference" estimate of -17.6% based on OLS regression and 15.0% based on fixed effects regression. The OLS estimates suggests that around 25% of the difference in the numbers self-employed between current borrowers and non-borrowers can be attributed to selection effects (i.e. the difference 5.8%/23.4% as a percentage is 24.8%) and around 60% can be attributed to micro-credit (i.e. the difference 17.6%/23.4% as a percentage is 75.2%). The fixed effects estimates suggests that around 35% of the difference in the numbers employed-for pay between current borrowers and non-borrowers can be attributed to selection effects (i.e. the difference 7.6%/22.6% as a percentage is 33.6%) and around 55% can be attributed to micro-credit (i.e. the difference 15.0%/22.6% as a percentage is 66.4%). Again unlike what was found for Pakistan, around 25%-35% of the difference between current borrowers and non-borrowers can be attributed to selection effects while the between 55%-65% can be attributed to micro-credit.

4. **Concluding Comments**

This paper examined the relationship between micro-credit and employment. Proponents of micro-credit argue that micro-credit is poverty-reducing in the sense that it leads to more household members being employed. With more household members working, more income is generated, which reduces the risk of poverty. Our view is that this mechanism is at best misleading. We test the hypothesis that micro-credit may cause a substitution of employment away from employment-for-pay to self-employment. If this is the case, then impact of micro-credit on total employment is ambiguous.

This hypothesis was tested with household-level survey data for Pakistan and Bangladesh based on a quasi-experimental design. This data was used to test for differences in self-employment across three groups of borrowers: Current borrowers, Pipeline borrowers and Non-borrowers. The inclusion of Pipeline borrower is a way of potentially controlling for self-selection effects. If these self-selection effects are large, then a comparison of only current borrowers and non-borrowers likely exaggerates the impact of micro-credit on employment. The models were estimated by OLS and fixed effects regression. The inclusion of fixed effects based on geographic regions (i.e. Union Councils and Thanas) provide an additional control for unmeasured differences in employment opportunities based on the area where the household is located.

The findings were mixed in the sense that the findings for Pakistan and Bangladesh were quite different. For Pakistan there no robust statistical evidence suggesting that micro-credit effects increasing employment were found. Selection effects were found to be large. In addition, the estimates varied considerably depending on whether OLS or fixed effect regression was used. This suggests that regional-specific factors, such as the quantity and quality of arable land, are likely important in the observed employment differences across households. While the Pakistan analysis is disappointing in terms of the main hypothesis, there is robust statistical evidence in support of it in Bangladesh. However, it is important to note that sizeable selection effects are also found but these effects are much smaller than what was found for Pakistan. In addition, the estimates are very similar for both OLS and fixed effects regression. This suggest that regional-specific factors are of less importance. For Bangladesh, based on fixed effects regression, micro-credit is associated with a 23% higher level of self-employment; a 7.2% lower level of employment-for-pay; and a 5.6% higher level of total employment [See Column (4) in Table 6].

It must be remembered that the data used in the analysis was based on the same quasi-experimental design. It is therefore of concern that the findings for the two countries are not similar. However, the overall analysis does suggests that it is potentially important to distinguish between different types of employment. One benefit of doing this is that it helps understand the mechanisms by which micro-credit impacts on poverty. Therefore surveys aimed at evaluating the micro-credit impacts will need to collect in details for all household members the type of work they are doing. We expect that in reality a share of adults in poor Pakistani and Bangladeshi households combined self-employment with employment-for-pay but only report to interviewers their main type of employment.

As was mentioned above, the age and sex structure of the household is important to the understanding of employment differences across households. At the simplest level, this suggests (not surprisingly) that large households have more household members employed. The number of adult female and male household and the number of adult older male household members is especially important in this respect. It is important to note that the number of male and female children in the household is not important. In most of the regression models summarised in Tables (3), (4) and (5), the number of children in the household variables were not statistically significant. In the few number of cases where this was not the case, the sign of relationship was negative. This provides some indirect evidence that micro-credit does not lead to higher levels of child employment. However, to fully appreciate the effect that micro-credit has on employment, analysis must be carried that not examines for employment-for-pay and self-employment separately by age and sex.

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Table 1
Numbers Employed by Borrower Group
Means [and Standard Deviations]
Pakistan and Bangladesh

Pakistan	**All**	**Current Borrowers**	**Pipeline Borrowers**	**Non-borrowers**	**F-test**
(a) Self-employed	*2.2 [1.6]*	*2.3 [1.5]*	*2.4 [1.7]*	*1.6 [1.3]*	*4.9******
(b) Employed-for-pay	*0.6 [1.0]*	*0.6 [0.9]*	*0.5 [0.8]*	*0.9 [1.4]*	*3.8**
Both (a) + (b)	*2.8 [1.7]*	*2.8 [1.6]*	*2.9 [1.9]*	*2.5 [1.5]*	*0.9*
N	*468*	*243*	*133*	*92*	
Bangladesh					
(a) Self-employed	*0.6 [0.7]*	*0.7 [0.8]*	*0.6 [0.7]*	*0.5 [0.7]*	*12.1******
(b) Employed-for-pay	*0.9 [0.8]*	*0.7 [0.8]*	*0.9 [0.9]*	*0.9 [0.8]*	*6.6******
Both (a) +(b)	*1.6 [0.8]*	*1.4 [0.8]*	*1.5 [0.8]*	*1.4 [0.7]*	*0.9*
N	*1,522*	*535*	*507*	*536*	

Notes: Statistical significance: "***" = 1% level; "**" = 5% level; and "*" = 10% level.

Table 2
Control Variables
Means [and Standard Deviations]
Pakistan and Bangladesh

Pakistan	**All**	**Current Borrowers**	**Pipeline Borrowers**	**Non-borrowers**	**F-test**
School	*3.80 [4.6]*	*3.8 [4.4]*	*4.9 [5.0]*	*2.2 [3.4]*	*6.1******
Age	*36.7 [11.0]*	*37.3 [10.8]*	*34.1[9.4]*	*37.8 [13.6]*	*3.5****
nChildF	*1.9 [1.8]*	*1.7 [1.8]*	*2.0 [1.8]*	*1.8 [1.6]*	*3.6****
nChildM	*2.1 [2.0]*	*1.9 [2.1]*	*2.1 [2.0]*	*2.2 [1.9]*	*1.5*
nAdultF	*2.3 [1.5]*	*2.2 [1.5]*	*2.4 [1.6]*	*2.3 [1.5]*	*0.4*
nAdultM	*2.5 [1.7]*	*2.6 [1.6]*	*2.5 [1.9]*	*2.5 [1.5]*	*0.2*
nOlderF	*0.1 [0.4]*	*0.1 [0.4]*	*0.1 [0.3]*	*0.1 [0.3]*	*2.2***
nOlderM	*0.2 [0.37]*	*0.2 [0.4]*	*0.2 [0.4]*	*0.1 [0.4]*	*0.7*
Household size	*9.0 [5.2]*	*8.6 [5.4]*	*9.3 [5.5]*	*8.9 [4.7]*	*1.5*
N	*468*	*243*	*133*	*92*	
Bangladesh					
School	*4.5 [4.2]*	*4.4 [3.8]*	*4.9 [4.3]*	*4.6 [4.5]*	*2.4***
Age	*42.8 [10.9]*	*43.1 [9.6]*	*42.6 [10.8]*	*42.6 [11.2]*	*0.4*
nChildF	*07 [0.8]*	*0.8 [0.9]*	*0.6 [0.8]*	*0.7 [0.8]*	*4.7******
nChildM	*0.8 [0.8]*	*0.9 [0.9]*	*0.7 [0.7]*	*0.7 [0.8]*	*7.1******
nAdultF	*1.3 [0.6]*	*1.3 [0.6]*	*1.3 [0.6]*	*1.2 [0.6]*	*3.9******
nAdultM	*1.4 [0.8]*	*1.4 [0.8]*	*1.4 [0.7]*	*1.3 [0.8]*	*5.8******
nOlderF	*0.06 [0.2]*	*0.05 [0.2]*	*0.06 [0.2]*	*0.06 [0.3]*	*0.2*
nOlderM	*0.1 [0.3]*	*0.08 [0.3]*	*0.1 [0.3]*	*0.1 [0.3]*	*1.0*
Household size	*4.3 [1.4]*	*4.5 [1.3]*	*4.2 [1.28]*	*4.0 [1.4]*	*18.1******
N	*1,522*	*517*	*517*	*509*	

Notes: Statistical significance: "***" = 1% level; "**" = 5% level; and "*" = 10% level.

Table 3
Regression Estimates
Total Number of Household Members Employed
Pakistan and Bangladesh

	(1)	(2)	(3)	(4)
Country	**Pakistan**	**Bangladesh**	**Pakistan**	**Bangladesh**
Fixed effects	**No**	**No**	**Yes**	**Yes**
Variable:				
Current	*0.101*** [2.1]*	*0.062* [1.7]*	*0.244 [0.8]*	*0.063* [1.7]*
Pipeline	*-0.067 [1.2]*	*0.007 [0.2]*	*0.193 [0.7]*	*0.009 [0.3]*
ln(Age)	*0.063 [1.0]*	*0.217*** [3.0]*	*0.102 [1.6]*	*0.233*** [3.2]*
ln(School)	*-0.001 [0.1]*	*-0.036*** [5.6]*	*0.015 [0.8]*	*-0.035*** [5.3]*
ln(nChildF)	*-0.067** [2.1]*	*-0.058* [1.7]*	*0.063* [1.9]*	*-0.053 [1.5]*
ln(nChildM)	*0.077** [2.4]*	*0.051 [1.5]*	*0.047 [1.4]*	*0.047 [1.4]*
ln(nAdultF)	*0.246*** [4.2]*	*0.430*** [6.2]*	*0.238*** [3.9]*	*0.432*** [6.3]*
ln(nAdultM)	*0.631*** [11.5]*	*1.321*** [23.9]*	*0.638*** [11.2]*	*1.303*** [23.6]*
ln(nOlderF)	*0.049 [0.5]*	*0.136 [1.3]*	*-0.009 [0.1]*	*0.164 [1.6]*
ln(nOlderM)	*0.279*** [2.9]*	*0.939*** [10.8]*	*0.297*** [3.1]*	*0.942*** [10.9]*
Constant	*-0.601** [2.6]*	*-0.850*** [3.4]*	*-0.830** [2.6]*	*-0.898*** [3.6]*
R^2(%)	*49.8*	*40.9*	--	--
N	*468*	*1,522*	*468*	*1,522*

Notes: (1) Absolute value of t-statistic in parentheses. (2) Statistical significance: "***" = 1% level; "**" = 5% level; and "*" = 10% level.

Table 4
Regression Estimates
Total Number of Household Members Employed-for-pay
Pakistan and Bangladesh

	(1)	(2)	(3)	(4)
Country	**Pakistan**	**Bangladesh**	**Pakistan**	**Bangladesh**
Fixed effects	**No**	**No**	**Yes**	**Yes**
Variable:				
Current	*-0.157**** *[2.9]*	*-0.148**** *[3.0]*	*-0.179* *[0.6]*	*-0.143**** *[3.0]*
Pipeline	*-0.212**** *[3.5]*	*-0.059* *[1.2]*	*-0.258* *[0.8]*	*-0.063* *[1.3]*
ln(Age)	*-0.046* *[0.7]*	*0.091* *[0.9]*	*-0.079* *[1.1]*	*0.107* *[1.1]*
ln(School)	*0.012* *[0.6]*	*-0.038**** *[4.4]*	*-0.018* *[0.8]*	*-0.035**** *[4.1]*
ln(nChildF)	*-0.068** *[1.9]*	*-0.077** *[1.7]*	*0.091**** *[2.4]*	*-0.077** *[1.7]*
ln(nChildM)	*-0.070* *[1.9]*	*0.077** *[1.7]*	*-0.009* *[0.3]*	*0.081** *[1.8]*
ln(nAdultF)	*0.0227**** *[3.4]*	*0.242**** *[2.6]*	*0.214**** *[3.1]*	*0.245**** *[2.7]*
ln(nAdultM)	*0.208**** *[3.4]*	*0.665**** *[9.0]*	*0.202**** *[3.2]*	*0.671**** *[9.1]*
ln(nOlderF)	*-0.179* *[1.6]*	*0.077* *[0.6]*	*-0.138* *[1.2]*	*0.115* *[0.8]*
ln(nOlderM)	*0.0340**** *[3.2]*	*0.556**** *[4.8]*	*0.307**** *[2.9]*	*0.559**** *[4.9]*
Constant	*0.123* *[0.5]*	*-0.203* *[0.6]*	*0.243* *[0.7]*	*-0.281* *[0.8]*
R^2(%)	*17.9%*	*10.9*	--	--
N	*468*	*1,522*	*468*	*1,522*

Notes: (1) Absolute value of t-statistic in parentheses. (2) Statistical significance: "***" = 1% level; "**" = 5% level; and "*" = 10% level.

Table 5
Regression Estimates
Total Number of Household Members Self-employed
Pakistan and Bangladesh

	(1)	(2)	(3)	(4)
Country	**Pakistan**	**Bangladesh**	**Pakistan**	**Bangladesh**
Fixed effects	**No**	**No**	**Yes**	**Yes**
Variable:				
Current	*0.249**** *[5.4]*	*0.210**** *[4.8]*	*0.288* *[1.1]*	*0.204**** *[4.8]*
Pipeline	*0.271**** *[5.3]*	*0.066* *[1.5]*	*0.296* *[1.1]*	*0.073** *[1.7]*
ln(Age)	*0.089* *[1.5]*	*0.126* *[1.5]*	*0.136*** *[2.5]*	*0.126* *[1.5]*
ln(School)	*-0.001* *[0.1]*	*0.001* *[0.2]*	*0.032*** *[1.9]*	*0.0003* *[0.04]*
ln(nChildF)	*0.015* *[0.5]*	*0.019* *[0.5]*	*-0.002* *[0.1]*	*0.025* *[0.6]*
ln(nChildM)	*0.091**** *[3.0]*	*-0.026* *[0.6]*	*0.038* *[1.3]*	*-0.036* *[0.9]*
ln(nAdultF)	*0.070* *[1.3]*	*0.188*** *[2.3]*	*0.083* *[1.6]*	*0.188*** *[2.3]*
ln(nAdultM)	*0.368**** *[7.1]*	*0.657**** *[1.0]*	*0.375* *[7.5]*	*0.628**** *[9.5]*
ln(nOlderF)	*0.188*** *[1.9]*	*0.059* *[0.5]*	*0.121* *[1.3]*	*0.047* *[0.4]*
ln(nOlderM)	*-0.001* *[0.1]*	*0.383**** *[3.7]*	*0.036* *[0.4]*	*0.383**** *[3.7]*
Constant	*-0.084* *[0.4]*	*-0.648*** *[2.1]*	*-0.273* *[1.0]*	*-0.613*** *[2.0]*
R^2(%)	*28.3*	*11.4*	--	--
N	*468*	*1,522*	*468*	*1,522*

Notes: (1) Absolute value of t-statistic in parentheses. (2) Statistical significance: "***" = 1% level; "**" = 5% level; and "*" = 10% level.

Table 6
Marginal Effects of Micro-credit on Employment
Pakistan and Bangladesh

	(1)	(2)	(3)	(4)
Country	**Pakistan**		**Bangladesh**	
(A) Both (Employed-for-pay and self-employed)				
Fixed effects?	**No**	**Yes**	**No**	**Yes**
Current borrowers	*10.6%*	*27.6%*	*6.4%*	*6.5%*
Pipeline borrowers	*6.9%*	*21.3%*	*0.7%*	*0.9%*
Difference	*3.7%*	*6.3%*	*5.7%*	*5.6%*
(B) Employed-for-pay				
Current borrowers	*-14.5%*	*-16.4%*	*-13.8%*	*-13.3%*
Pipeline borrowers	*-19.1%*	*-22.7%*	*-5.7%*	*-6.1%*
Difference	*4.6%*	*6.4%*	*-8.1%*	*-7.2%*
(C) Self-employed				
Current borrowers	*28.3%*	*33.4%*	*23.4%*	*22.6%*
Pipeline borrowers	*31.1%*	*34.4%*	*5.8%*	*7.6%*
Difference	*-2.9%*	*-1.1%*	*17.6%*	*15.1%*

Notes: Marginal effect = *[exp(α)-1] x 100,* where α are the estimated parameters values for the micro-credit variables given in Tables 3-5. See text for further details