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The impact of microcredit borrowing on household consumption in Bangladesh

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ABSTRACT

The rapid expansion of microcredit in recent years renders knowledge of its impact on poverty critical. Unfortunately, empirical investigations have been limited by endogeneity issues, and randomized controlled trials suffer from a lack of power. This article suggests a strategy for handling the endogeneity of microcredit borrowing without specifying instrumental variables, allowing for estimation using observational data. The model is identified by an assumption on the conditional second moments of the errors and estimated semiparametrically. I find that an increase in the amount borrowed from the Grameen Bank and similar institutions in Bangladesh has a positive and significant effect on per-capita household consumption. The estimated elasticity is in the range of 0.18 to 0.21. These estimates indicate that microcredit may be more effective than previously thought.

KEYWORDS
Semiparametric estimation; heteroscedasticity; endogeneity; microfinance

JEL CLASSIFICATION
O16; O22; C14

I. Introduction

Microcredit is considered by many practitioners and advocates to be a powerful tool to alleviate poverty. The practice consists of lending small amounts to the very poor for self-employment projects, known as microentrepreneurship, with the intention of allowing households that would otherwise be credit constrained to engage in income-generating activities. The Grameen Bank and its founder, Muhammad Yunus, were awarded the Nobel Peace Prize in 2006 for originating this method of ”development from below”, and the model has spread around the world, reaching an estimated 175 million people (Microcredit Summit Campaign). Despite its popularity, however, little to no empirical evidence exists of the effectiveness of microcredit at reducing poverty.

Microcredit institutions often package loans with services such as job training, but empirical studies have focused on household poverty, as measured by per-capita household consumption,[1] as an outcome of fundamental importance. Microcredit loans often carry high interest rates, and Grameen Bank-style joint liability, in which all members of a borrowing group are excluded from future loans if one member defaults, drives repayment rates to an average of over 90% (Grameen Foundation). Critics worry that these features mean microcredit could ultimately make borrowers even poorer. If microentrepreneurs are unable to earn profits and pay off their loans, they may become stuck in a debt trap and resort to selling off assets or borrowing from other sources to make the payments.

A particularly relevant question for donors and practitioners is how a microcredit loan would affect the consumption of a randomly selected household in the population of interest. Many organizations, including the World Bank, the United Nations and USAID, have stated goals of increasing the usage of microcredit in developing countries. In particular, during the years since the survey data used here were collected in Bangladesh, microcredit institutions have continued to open branches across the country. It is therefore important to ask not just how loans have benefited those who were first to join microcredit groups, but how they can be expected to benefit an average household.

The difficulty in estimating this effect arises because households that have already borrowed are not a random sample of the population. Households decide whether or not to take out a loan and start a business based on unobserved attributes such as entrepreneurial ability. In

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[1]See Ravallion (1992) for a discussion of consumption as a measure of poverty

addition, microcredit institutions are targeted towards poorer households. Various techniques have been employed in the literature to try to identify the expected impact of microcredit borrowing on a random household. As discussed below, quasi-experimental survey designs have been employed to create an appropriate control group of people who were excluded from borrowing. More recently, randomized controlled trials have been developed and implemented.

Rather than relying on randomization, in this article, I adopt a new approach to identifying the impact of microcredit borrowing. I estimate the effect of the amount borrowed from a microcredit institution on per-capita household consumption in Bangladesh. Identification relies on the assumption that the conditional correlation between the errors in the borrowing and consumption equations is constant; I outline a plausible error structure that satisfies this requirement. Under this assumption, the model is identified in the presence of heteroscedasticity. This approach has the advantage of using observational data, which could allow the evaluation of a broader array of programmes around the world. In addition, the observational dataset described below allows for the evaluation of microcredit borrowing over a longer time frame than is possible with data from existing randomized trials.

II. Literature

Attempts to model household consumption as a function of microcredit borrowing have focused on ways to overcome the endogeneity of borrowing. Households select into borrowing based not only on their observed characteristics but also on unobserved traits such as entrepreneurial ability. Microcredit institutions choose where to locate and what type of households to target, perhaps using information that is not observable to the econometrician. These unobserved characteristics can also be expected to affect consumption directly, biasing estimates of the impact of borrowing that do not account for the endogeneity. The empirical literature on this topic has until recently been quite scarce, reflecting a failure to find instrumental variables that affect borrowing but not consumption.

Pitt and Khandker (1998) was one of the first significant attempts to study the impact of microcredit borrowing on household outcomes, and their results are often cited by both academics and practitioners. Using the intuition of a regression discontinuity to generate exclusion restrictions, they estimate the impact of borrowing from three different microfinance institutions in Bangladesh: the Grameen Bank, the Bangladesh Rural Advancement Committee (BRAC), and the Bangladesh Rural Development Board's (BRDB) Rural Development RD-12 programme. Estimating the impact of loans from these three institutions to both men and women, they find elasticities of per-capita household consumption with respect to the six resulting sources of borrowing ranging between 0.018 and 0.043.

Identification in Pitt and Khandker comes from a lending rule that was, at least nominally, followed by all three microfinance institutions in Bangladesh at the time of the survey. Only households that were "functionally landless", defined as owning less than one-half acre of land, were considered eligible for microfinance loans. The assumption is that there should be a discontinuity in borrowing at one-half acre of land, but no discontinuity in household consumption at the cut-off point, conditional on borrowing. Using this requirement to divide households into groups based on borrowing eligibility, Pitt and Khandker are able to identify the effect of borrowing in a limited-information maximum likelihood estimation. The authors point out that the same identifying assumptions could be used to implement a two-stage least-squares estimation, in which a dummy variable for whether a household faced the choice to borrow is interacted with all of the exogenous variables to generate instruments for borrowing.

There has been some debate over the validity of this identifying assumption. Most notably, Roodman and Morduch (2014) argue that there was mistargeting in lending, in the sense that the landholding rule was not enforced. In response, Pitt (2014) defends the identification strategy and provides additional specification tests. I contribute to this debate in a broader sense by looking for evidence of microcredit effectiveness in the same data but using an alternative source of identification.[2]

The implementation of randomized trials is the most recent strategy employed to deal with the endogeneity of borrowing. A special issue of the *American Economic Journal: Applied Economics* contained the results of six randomized evaluations of microcredit programmes. The results are similar, in that they find small or null results across a range of countries and contexts. Of these six evaluations, four look at household consumption as an outcome. Banerjee et al. (2015) discuss an experiment in Hyderabad, India, where new microfinance institutions were opened in a randomly selected half of a group of slums. Within each location, households could then endogenously form groups and choose to borrow. The treatment status of a slum provides an exclusion restriction, affecting borrowing, but not consumption conditional on borrowing. The authors estimate the impact of living in a treatment area 15 to 18 months after the branches were opened, and find no effect of access to microcredit on average per-capita expenditure. They do find increases in durable expenditures in households with existing businesses and those that were likely to start a business, however, suggesting that investment was taking place, and that greater impacts may be found as time goes on.

Two of the other studies also estimate intent-to-treat effects on consumption and find relatively precise null effects (Attanasio et al. (2015) and Crépon et al. (2015)). Augsburg et al. (2015), is the only one of the six studies that randomized at the individual level, using a credit-scoring approach similar to earlier work by Karlan and Zinman (2010), and Karlan and Zinman (2011). They find a significant decrease in household consumption, which could be due to repayment of initial loans, again allowing for the possibility that positive impacts could be found in later time periods.

In a summary of these six papers, Banerjee, Karlan, and Zinman (2015) offer a few potential reasons that the studies could be failing to pick up positive effects of microcredit, if such effects indeed exist. Power is a particular challenge in evaluations that randomize at the level of programme placement, due to low rates of programme take-up. In addition, identification is limited to the intent-to-treat effect, and the authors note that most of the null results do not imply precise estimates of treatment-on-the-treated effects (in other words, the effects for actual borrowers). Finally, the timeframe over which the loans are evaluated is relatively short, with the longest being around three years. The authors note that it is challenging to extend the time horizon of such an experiment, as it requires justification of withholding loans from control households for longer periods of time.

Dahal and Fiala (2020) pool the data from these six RCTs and two others, and estimate effects over the full sample. After noting that the coefficients in the individual studies are mostly large but insignificant, they find that every one of the experiments is underpowered to detect effects of a reasonable magnitude. In the pooled sample, they find positive and significant impacts on revenues, profits, and household assets, although not consumption.

To draw broader conclusions about the impact of microcredit over longer time frames and in additional countries, it would be beneficial to combine the results from these studies with estimates from observational datasets. Estimation of different parameters is also of interest, allowing for analysis of the impact on individual borrowers as well as community-level effects. I return to the Bangladesh data used by Pitt and Khandker, and Morduch and Roodman, and estimate the impact of borrowing on consumption by proposing an identification strategy that is new to the microcredit literature.

III. Estimation and identification strategy

A new approach to identifying models in the absence of exclusion restrictions is to make an alternative assumption about the unobservables. In the absence of credible instruments, other literatures have looked for different types of moment conditions that can reasonably be imposed to identify sample selection models. For example, many impact evaluations use propensity score methods

[2]Another example of a quasi-experimental design is Coleman (1999), who identifies the average effect of a programme in Thailand by exploiting the fact that some households that had selected into borrowing groups had not yet received their loans. He does not find a significant average effect of treatment status on household income but notes that the population in Thailand is wealthier than that of countries such as Bangladesh, and access to other sources of credit is more widespread.

to compare people in the treated group to people with similar characteristics who did not receive treatment. Estimation of this type involves assuming that treatment status is independent of the outcome of interest, conditional on the probability of receiving treatment. This assumption is not realistic in the context of microcredit, however, as households select into borrowing based on unobservable characteristics that also affect consumption. Biased estimates of the impact of borrowing will result unless selection on unobservables is also controlled for.

An example from the education literature, Altonji, Elder, and Taber (2005), suggests imposing that selection on the observables is equal to selection on the unobservables. Here, the impacts of the observed part of the outcome equation and the unobserved part of the outcome equation on the endogenous variable are assumed to be equal. The authors argue that the assumptions necessary to motivate this condition are no less plausible than the assumption, made when using OLS or probit methods, that selection on the unobservables is zero, and show that estimates using this moment condition can provide a lower bound on the impact of the endogenous variable.

I adapt control-function methods, discussed below, by imposing another restriction that has been applied in the education literature. The missing moment condition caused by the endogenous variable is replaced with a condition on the second moments of the errors in the model. This identification strategy, proposed by Klein and Vella (2010), has been used parametrically or semiparametrically to estimate returns to schooling by Klein and Vella (2009), Farré, Klein, and Vella (2012, 2013), and Saniter (2012). A related estimator by Klein and Vella (2009) that can be applied to endogenous binary treatment models has been used by Emran and Sun (2015) and Bentancor and Robano (2014); Berg, Emran, and Shilpi (2015) apply this estimator to find the effects of competition from microfinance on moneylender interest rates.[3]

Estimation does not require the use of instruments but instead relies on the presence of heteroscedasticity in the estimating equations. Identification is based on the restriction that the correlation coefficient of the disturbances, conditional on the exogenous regressors, is constant. I outline a plausible error structure that satisfies this requirement below.

Consider the following system of borrowing and consumption equations. Per-capita household consumption depends on the amount borrowed, B, and a set of additional household characteristics, X, that are assumed to be exogenous. These include demographic characteristics such as the sex and age of the household head, and the education levels of household members. Borrowing also depends on a set of exogenous characteristics, Z. For expositional purposes, Z is the time being allowed to contain a variable that is excluded from X. Borrowing is measured as the total amount borrowed over the past seven years and is censored at the minimum loan amount, $\underline{B}$, of 1000 taka.[4]

$$C_i = X_i\beta + \delta B_i + u_i \tag{1}$$

$$B_i^* = Z_i\pi + v_i \tag{2}$$

$$B_i = \begin{cases} B_i^* \text{ if } B_i^* > \underline{B} \\ 0 \text{ otherwise} \end{cases} \tag{3}$$

The endogeneity of borrowing arises due to the correlation between the error terms, u and v, caused by the unobservable factors that affect both borrowing and consumption.

Models encompassing endogeneity combined with Tobit-type censoring have been considered in the parametric and semiparametric literature. Vella (1993) describes a two-step estimation procedure for estimating the system of equations above, under the assumption that the errors are jointly normally distributed. Taking conditional expectations of Equation (1) gives

$$E[C_i|X_i, B_i] = X_i\beta + \delta B_i + E[u_i|X_i, B_i] \tag{4}$$

Using the assumption of joint normality and the law of iterated expectations, the last term can be rewritten.

$$E[u_i|X_i, B_i] = E[E[u_i|Z_i, v_i]|X_i, B_i] \tag{5}$$

[3]Other examples of identification by heteroscedasticity are estimators developed by Rigobon (2003) and Lewbel (2012), which have been applied by Emran and Hou (2013), Emran and Shilpi (2012), Gilchrist and Zakrajsek (2013), and Rigobon and Rodrik (2005).

[4]While it would be desirable to isolate the effects of borrowing in different years, borrowing from year to year is too highly correlated to be able to make any definitive statements about each year separately.

$$= \rho E[v_i|Z_i, B_i] \tag{6}$$

where $\rho = \frac{cov(u,v)}{var(v)}$. The equation to be estimated becomes

$$C_i = X_i\beta + \delta B_i + \rho E[v_i|Z_i, B_i] + e_i \tag{7}$$

The remaining error term e, is uncorrelated with v by construction: $e = u - \frac{cov(u,v)}{var(v)}v$. The conditional expectation of v, however, is unobserved and correlated with the other regressors. Employing a consistent estimate of this expectation as a control function removes the impact of v on u, restoring orthogonality of the regressors. Under the normality assumption, Equation (3) can be estimated by Tobit, and the appropriate control function is the Tobit generalized residual, given by

$$\tilde{v}_i = E[v_i|Z_i, B_i] = -\hat{\sigma}_v(1 - I_i)\phi_i(1 - \Phi_i)^{-1} + I_i\widehat{v}_i \tag{8}$$

The last term, $\widehat{v}_i = B_i - Z_i\hat{\pi}$, is the residual for observations with positive amounts of borrowing. Additionally, $\hat{\sigma}_v$ and $\hat{\pi}$ are the Tobit estimates, ϕ_i and Φ_i are the probability density function and cumulative distribution function of the standard normal distribution evaluated at these estimates, and I_i is an indicator that is equal to one if borrowing is positive. Consistent parameter estimates can be obtained by estimating the following equation by least squares.

$$C_i = X_i\beta + \delta B_i + \rho\tilde{v}_i + e_i \tag{9}$$

In the absence of an exclusion restriction requiring that a variable in Z does not appear in X, this equation is identified only by the nonlinearity of the normal distribution.

A related model is a sample selection model in which consumption is only observed for households that have borrowed positive amounts. This group of households is expected to be different from the full sample. After controlling for the X variables, selection into the positive borrowing group is caused by v, leading to sample selection bias if u and v are correlated. Since the factors in v are responsible for both sample selection and the endogeneity of borrowing, however, one control function can be used to control for both. Equation (9) can be consistently estimated over the subsample of observations with positive amounts of borrowing, noting that the residual for these observations is $\widehat{v}$. The control function purges the error term of the component that is correlated with borrowing, including factors that lead to selection into the positive borrowing group. In this case, however, an exclusion restriction would be necessary. The residual, $\widehat{v}$, would otherwise be a perfect linear combination of the variables in X and the borrowing variable, and the matrix of regressors would not be of full rank.

The assumption that the errors in Equations (1) and (2) are normally distributed can be relaxed. Lee and Vella (2006) propose a semiparametric least-squares estimator for this system of equations, which relies on the same idea of removing the impact of v on Equation (1) by conditioning on an estimate of its conditional expectation. This approach also requires the assumption of an exclusion restriction.

These control function approaches could be employed in the present application in the presence of an exclusion restriction. However, the scarcity of empirical literature on microcredit so far reflects the failure to find such exclusions. Many of the obvious candidates have been ruled out. Interest rates cannot be used as instruments since these rates generally do not vary within programmes. Community characteristics cannot be used when community-level fixed effects are included to control for non-random programme placement (Armendariz and Morduch (2005) discuss these points). Finally, there are no obvious household characteristics that can be assumed a priori to affect borrowing but not consumption.

Accordingly, assume that $Z = X$ in Equations (1) through (3). The lack of identification in Equation (1) is the result of having one more parameter to estimate than moment conditions to impose on the data. Since orthogonality of borrowing and the error term cannot be justified, an additional moment condition is needed to identify the model. The literature on microcredit to date has approached this problem by looking for additional moment conditions involving the first moments of borrowing and consumption, generating instruments either by randomization or survey design. The strategy of Klein and Vella focuses on second moments. Variation in X provides an additional source of identification when the distribution of the error terms depends on the exogenous variables.

To see how this strategy enables identification, assume the errors are heteroscedastic and can be written as follows.

$$u = S_u(X)u^* \tag{10}$$

$$v = S_v(X)v^* \tag{11}$$

$$E[u|X] = E[v|X] = 0 \tag{12}$$

Here, $u*$ and $v*$ are assumed to be homoskedastic, and the conditional variances are given by

$$var(u|X) = S_u^2(X) \tag{13}$$

$$var(v|X) = S_v^2(X) \tag{14}$$

In Equation (7), the impact of the control function on consumption was given by

$$\rho = \frac{cov(u, v)}{var(v)} \tag{15}$$

When the conditional second moments of the errors depend on X, however, the impact of the control function is no longer constant. Define

$$A(X) = \frac{cov(u, v|X)}{var(v|X)} \tag{16}$$

The equation to be estimated is now identified without exclusion restrictions.

$$C_i = X_i\beta + \delta B_i + A(X)\widehat{v}_i + \varepsilon \tag{17}$$

Unlike Equation (9), the matrix of regressors here is of full rank, as long as the impact of the control varies with X. Equation (17) can be estimated over the sample for which $B_i > 0$, provided consistent estimation of $A(X)$.

Klein and Vella show that estimation is possible when the errors satisfy the following constant correlation condition.

$$E[u^*v^*|X] = E[u^*v^*] \tag{18}$$

When this condition holds, $A(X)$ can be rewritten.

$$A(X) = \rho_0 \frac{S_u(X)}{S_v(X)} \tag{19}$$

where $\rho_0 \equiv \frac{cov(u^*,v^*)}{var(v^*)}$ is constant. Provided consistent estimates of the conditional variances of u and v, the equation of interest can now be estimated as

$$C_i = X_i\beta + \delta B_i + \rho_0 \frac{S_u(X)}{S_v(X)} \widehat{v}_i + \varepsilon_i \tag{20}$$

The model is identified as long as $S_u(X)$ and $S_v(X)$ are not identical functions. I assume a reasonable structure for the errors that possesses the constant correlation property, which is discussed in detail below.

Estimation is done in two stages. First, the borrowing equation is estimated over the entire sample of households who faced a choice to borrow. The borrowing equation is estimated by the semiparametric least-squares method of Ichimura (1993). This technique allows for censoring without requiring homoskedasticity or normality of the error terms. Ichimura describes how a Tobit-type model can be described as a single-index model, in which the distribution of the error term, v, can depend on the index. The necessary assumption is thus that the same index of characteristics is driving selection into borrowing and the amount borrowed, as well as the heteroscedasticity.[5] Estimates of π in Equation (2) are obtained as:

$$\hat{\pi} = \arg\min_{\pi} \sum_{i=1}^{n} \left(B_i - \hat{E}[B_i|X_i\pi]\right)^2 \tag{21}$$

The operator $\hat{E}[\cdot]$ is a nonparametric conditional expectation, estimated using a normal kernel and Silverman plug-in bandwidth. Since these estimators are identified up to location and scale, $X_i\pi$ is an index of the X's in which the constant is normalized to zero, and the coefficient on a continuous variable in X is normalized to one.

The residuals from this estimation are used to compute the conditional variance of the borrowing error. For households with positive amounts of borrowing, the residuals from the first stage estimation are simply $\widehat{v} = X\hat{\pi}$. Once residuals have been obtained for these households, they are used to

[5]This equation could also be estimated under these assumptions using the symmetrically trimmed least-squares estimator of Powell (1986), without requiring the heteroscedasticity to be a function of the index. Using this technique resulted in a severe loss of precision, however, due to the amount of data that is thrown out by trimming the positive observations.

estimate S_v^2. This is done by taking the nonparametric expectation of $\widehat{v}^2$ conditional on $X\hat{\pi}$, in order to maintain the index assumption on the heteroscedasticity.

$$\hat{S}_{vi}^2 = \hat{E}\left[\hat{v}_i^2 | X_i \hat{\pi}\right] \tag{22}$$

In the second stage, the primary equation is estimated over the subsample of households that borrowed positive amounts. The functional form of $S_u(\cdot)$ is unspecified. Although it is possible to estimate $S_u(\cdot)$ nonparametrically, it is more practical to assume an index structure, allowing parameters to be well identified using a reasonable amount of data. The index restriction is that $S_u^2(X_i) = S_u^2(X_i\gamma)$.

$$C_i = X_i\beta + \delta B_i + \rho_0 \frac{S_u(X_i\gamma)}{\hat{S}_v} \hat{v}_i + \varepsilon_i \tag{23}$$

Klein and Vella (2010) provide a semiparametric estimation procedure for this equation, which estimates the index parameters of the conditional variance simultaneously with the other parameters of interest. First, define

$$u_i(\beta, \delta) = C_i - X_i\beta - \delta B_i \tag{24}$$

A variance-type estimator is defined as

$$S_{u_i}^2(\beta, \delta, \gamma) = E[u_i^2(\beta, \delta) | X_i\gamma] \tag{25}$$

Notice that at the true parameter values, $u_i(\beta_0, \delta_0) = u_i$ and $S_{u_i}^2(\beta, \delta, \gamma) = S_{u_i}^2(X_i)$. The conditional variance is estimated semiparametrically, where $\hat{E}[\cdot]$ is once again the nonparametric expectation using normal kernels.

$$\hat{S}_{u_i}^2(\beta, \delta, \gamma) = \hat{E}[u_i^2(\beta, \delta) | X_i\gamma] \tag{26}$$

Parameter estimates are obtained selecting β, δ, ρ_0 and γ to minimize the sum of the squared residuals of the resulting consumption equation.

$$C_i = X_i\beta + \delta B_i + \rho_0 \frac{\hat{S}_{u_i}(\beta, \delta, \gamma)}{\hat{S}_v} \hat{v}_i + \varepsilon_i \tag{27}$$

In each step, starting values are given by the OLS estimates. Standard errors are computed by 1,000 bootstrap repetitions, where each observation is sampled with replacement and both stages of the estimation, including the control function, are computed in each repetition.

Identification relies on the constant correlation assumption given by Equation (17). It is useful to think of potential error structures in the present example under which this assumption would or would not be satisfied. The literature on microcredit has focused on entrepreneurial ability as the driving force behind selection into borrowing and the endogeneity between borrowing and consumption. (Pitt and Khandker 1998; Coleman 1999; Armendariz and Morduch 2005). Armendariz and Morduch describe the household's endowment of entrepreneurship as 'entrepreneurial skills, persistence in seeking goals, organizational ability and access to valuable social networks' (p. 272). Individuals with more entrepreneurial tendencies are likely to borrow more, and also to earn higher incomes regardless of borrowing. Failure to control for entrepreneurial ability might therefore lead to an over-estimation of the effects of borrowing. Armendariz and Morduch cite a finding, from a survey done by Hashemi (1997), that over half of those who chose not to borrow from a microfinance programme in Bangladesh did so because they felt that they would not be able to generate sufficient profits to be able to repay the loans. In this sense, households appear to be selecting into borrowing based on their own assessments of their entrepreneurial ability.

One example of an error structure is therefore the assumption that the disturbances are comprised purely of entrepreneurial ability. In this case, the errors described by Equations (10)–(12) can be written as follows, where $a*$ denotes unobserved entrepreneurial ability.

$$u = S_u(X)a^* \tag{28}$$

$$v = S_v(X)a^* \tag{29}$$

There are a variety of ways that heteroscedasticity of this form can be expected to arise in the model. Consider the borrowing equation. The impact of entrepreneurial ability on borrowing is likely to be a function of the location variables. A higher variance of borrowing can be expected in locations that have more extensive microfinance institutions that have been in place longer. In these areas, high ability households will have had more opportunities to borrow greater amounts, so the effect of their ability will be magnified by a function of their location, $S_v(X)$. The availability of outside borrowing options also varies across areas and can be expected to affect the amount of microcredit borrowing demanded. High ability households may be able to obtain loans from traditional banks. Regional variation in the availability of traditional banks may therefore lead to different variances in the amount of borrowing from microcredit institutions in different areas. Microcredit institutions also increasingly target female borrowers. Thus, the impact of high ability would be magnified, as determined by $S_v(X)$, for households containing an adult woman.

The consumption equation contains potential sources of heteroscedasticity as well. Two households with equal endowments of ability may face different consumption opportunities if one is headed by a man and the other is headed by a woman. The impact of the ability term is magnified or diminished based on the gender of the head of the household, in a manner captured by $S_u(X)$. Thus, a higher variance in consumption might be expected in households headed by men. The set of regressors also includes the number of family members of the household head and spouse who own land, which is a measure of wealth. Having wealthier relatives may have a stabilizing effect that helps to guarantee a minimum amount of consumption, dampening the variance in consumption for those households and minimizing the impact of low ability. In addition, the set of location characteristics includes information that will affect incomes in an area, and households with higher income-generating opportunities will have a greater variance in consumption. For example, households with the same endowment of ability can earn higher incomes in areas with higher wages. Among households that produce milk or eggs, for example, those in areas with higher prices for milk and eggs will be able to earn higher incomes, increasing the variance of consumption.

If the unobserved error terms are purely comprised of entrepreneurial ability, as in Equations (28) and (29), the constant correlation assumption is satisfied trivially, and we would expect a positive correlation between the error terms. In the data, however, the correlation between u and v is found to be negative, both here and in Pitt and Khandker. A negative correlation between the error terms is also common in the literature on returns to education, where the presence of unobserved ability terms would, on its own, lead to a positive correlation. This suggests that there are other sources of endogeneity in the error terms. In the present application, one such source of unmeasured variation is random shocks to household income. For example, two households with equivalent endowments of ability may make different borrowing decisions if a member of one household becomes sick or injured. Such a shock could also cause a reduction in consumption, leading to a correlation between the error terms of the two equations. Similarly, random events such as flooding that destroys crops could also affect both borrowing and consumption. Microcredit programmes are specifically designed to appeal to the poorest borrowers, using devices such as small loan sizes and the requirement to enter into joint liability agreements, which households with other resources might find unattractive (Khandker 1998). This targeting will lead to a negative correlation between the unpredictable shock components of the error terms, since events that reduce potential consumption will also increase interest in borrowing. Denoting these shocks ε_1 and ε_2, and assuming a multiplicative structure, the errors become

$$u = S_u(X)a^*\varepsilon_1 \tag{30}$$

$$v = S_v(X)a^*\varepsilon_2 \tag{31}$$

Now ρ_0 in Equation (19) will depend on the correlation between the εs, and have a negative sign if this correlation is negative. This structure is the same as the one employed by Klein and Vella's returns to schooling estimation (2009), and satisfies the constant conditional correlation condition under the assumption that the εs are independent of X, as well as independent of $a*$.

To give some intuition, consider two households in which the head of household suffers a broken leg, reducing his ability to work. The assumption would be that this shock leads to a constant propensity to consume less, and a constant propensity to borrow more. The relationship between the borrowing and consumption propensities is captured by ρ_0. Each household's actual ability to adjust consumption and borrowing, however, depends on factors such as location. For instance, a household in an area with more access to microcredit could respond by borrowing more; this effect is captured by $S_v(X)$. Thus, while the correlation between ε_1 and ε_2 is constant, the correlation between u and v depends on the functions of X that magnify or diminish the impact of the εs in each equation. The conditional correlation assumption would not be satisfied, then, if failure to control for location effects led to the correlation between ε_1 and ε_2 that varied with location, which is potentially related to other variables in X. Below, I control for location effects in the estimation, first by including a set of location fixed effects and then using a set of village-level characteristics.

IV. Empirical model and results

The Household Study to Conduct Micro-Credit Impact Studies was carried out by the Bangladesh Institute of Development Studies (BIDS) and the World Bank between 1991 and 1992. The survey sampled 1,798 households drawn from 87 villages of 29 Thanas, or sub-districts, in rural Bangladesh. Out of the 29 Thanas, 24 had microfinance programmes in place at the time of the survey. The first stage of estimation is carried out over all households in these 24 programme Thanas, resulting in a sample size of 1,457 households. The second stage uses the subsample of 813 households with positive microcredit borrowing. Descriptive statistics are provided in Table 1. Results presented here use the dataset made available by Roodman and Morduch.[6]

Table 1. Summary statistics.

	Mean	Std. dev.
Annual per-capita houshold consumption (taka)	4507.21	2796.71
Total borrowng (taka)	2931.26	6843.77
Education of head	2.754	3.723
Age of head	41.266	13.153
Sex of head (male = 1)	0.950	0.219
Max education female	1.920	3.306
Max education male	3.627	4.234
No adult male present	0.033	0.178
No spouse present	0.117	0.321
No adult female present	0.010	0.101
No adult male present	0.033	0.178
Head's parents own land	0.254	0.559
# head's brothers own land	0.805	1.301
# head's sisters own land	0.802	1.256
Spouse's parents own land	0.514	0.780
# spouse's brothers own land	0.919	1.437
# spouse's sisters own land	0.765	1.20
Landholding	137.89	425.39

n = 1,457

The exogenous variables chosen are the same as those employed by Pitt and Khandker. Household characteristics include the age and sex of the household head, the education level of the household head, and the highest education level achieved by a male and female in the household. Dummy variables for the absence of an adult male and absence of an adult female are included to allow interpretation of these coefficients, as is a dummy for the presence of a spouse. Also included is a set of variables describing whether or not the parents of the household head and spouse own land, and the number of brothers and sisters of the head and spouse who own land. These variables are intended to control for outside opportunities for borrowing or income.

Location characteristics are controlled for in two ways. The first set of results includes a set of Thana dummy variables. The use of Thana dummies is a departure from the Pitt and Khandker model, which includes village fixed effects, but was a necessary reduction in dimensionality for the semiparametric estimations. Location characteristics that may affect both borrowing and consumption include not only observed features like price and infrastructure variables but unobserved attributes like proximity to an urban area, climate, and local attitudes. The location dummies will also absorb any spillover effects that the presence of a microcredit institution has on all residents, regardless of their borrowing status. It is possible, for example, that some of the increased expenditures by households that borrow will go towards buying goods and services from their neighbours. In this case, the presence of microcredit will raise the average consumption for all residents of a community. The coefficients on borrowing estimated here thus represent the benefit to a household that borrows over and above the benefits from any spillovers.

The second set of results includes a set of village characteristics. These include the average wages for men and women in each village, and a set of goods prices. Also included are variables that describe the local infrastructure, including the distance to

[6]http://www.cgdev.org/content/publications/detail/1422302.

a bank and the presence of schools, health clinics, and family planning and midwife services. This specification has the advantage of controlling for some location characteristics at a more local level but lacks the spillover interpretation given above. In each specification, the heteroscedasticity index for the consumption equation includes the same explanatory variables that appear in the conditional means of both equations.

A rough test for heteroscedasticity would be to use the OLS residuals. Table 2 shows the results of regressing the squared OLS residuals from the borrowing and consumption equations onto all the explanatory variables. Test results are reported under both model specifications. In all four cases, the null hypothesis of homoskedasticity is rejected. For the borrowing equation, the evidence of heteroscedasticity is strongest for the Thana dummy specification, indicating that regional variation in programme availability and intensity is an important source of heteroscedasticity. In the full control-function estimation, which produces consistent estimates of the residuals, the only available heteroscedasticity test is for the consumption equation. Here, it is possible to test the significance of the coefficients in the heteroskedasticity index, $S_u(X_i\gamma)$. These results, discussed below, also find evidence of heteroscedasticity in the consumption equation.

Table 3 presents the results of estimating the borrowing equation in the Thana dummy specification, showing the estimates of π in Equation (21). As discussed above, one of the index coefficients must be normalized to one. Given this normalization, the coefficients can only be interpreted in relative terms. Here, the coefficient fixed to unity is on the variable that gives the negative of log-landholding, since an increase in landholding is known to reduce the likelihood of borrowing, and the remaining coefficients will therefore have the correct sign. All household variables other than the sex of the household head have been standardized to have mean zero and standard deviation equal to one. Thus, looking only at the point estimates, an increase of one standard deviation in the maximum education of a male in the household is interpreted to have 75% of the impact of an increase of one standard deviation in the maximum education of a female.

Having a male head of household led to a significant reduction in the amount borrowed. This result is expected, since microcredit has become increasingly targeted towards women over the years in Bangladesh. Each borrowing group is required to be single-sex, and female-only groups were more prevalent in the survey areas, compounding the effect of targeting women by providing more opportunities for women to join groups. Households without an adult male or a spouse present borrowed less. This is evidence that entrepreneurship is easier for households that have two working age adults present, a household head and a spouse. The entrepreneurial good may be produced at the same time as home production, such as child care, making entrepreneurship feasible for households in which the spouse of the head does not work outside the home (Pitt and Khandker (1998) describe such a model of household production.). Households with more highly educated females borrowed less, although the coefficient was only significant at 10%; this pattern is perhaps an indication that these women were more likely to work before microcredit borrowing, and thus less

Table 2. Heteroscedasticity tests.

	Chi-squared	p-value
Borrowing equation		
Thana dummy	30.93	0.000
Village characteristics	9.34	0.002
Consumption equation		
Thana dummy	48.37	0.000
Village characteristics	40.65	0.000

Table 3. Dependent variable: log borrowing.

Education of head	0.209	(0.376)
Sex of head	−5.510***	(1.214)
Age of head	0.572	(0.654)
Max ed male	−0.377	(0.399)
Max ed female	−0.503*	(0.262)
No adult male present	−0.934***	(0.285)
No adult female present	−0.038	(0.200)
No spouse present	−0.889***	(0.281)
Head's parents own land	0.071	(0.232)
# head's brothers own land	−0.008	(0.228)
# head's sisters own land	0.113	(0.235)
Spouse's parents own land	−0.319	(0.248)
# spouse's brothers own land	−0.358	(0.240)
# spouse's sisters own land	0.093	(0.241)

Standard errors in parentheses, computed by 1,000 bootstrap iterations. *, **, *** denote 10%, 5% and 1% significance, respectively. n=1,457. Controls include set of Thana dummies.

inclined to microentrepreneurship. In addition, there is evidence that regional variation is an important determinant of borrowing, as several of the Thana dummy variables are significant.

The parameter estimates for the consumption equation are presented in Table 4. The first column shows the OLS estimates over the subsample of households with positive borrowing. Column three gives the estimates after inclusion of the control function, where the coefficient on log borrowing is δ, the coefficient on the control function is ρ_0, and the remaining coefficients are included in β in Equation (27). Here, parameter estimates are presented for the non-standardized variables. Some power is lost, but the signs of the coefficients on the household characteristics, with the exception of the sex of the head of household, are consistent with the OLS estimation. The elasticity of consumption with respect to land-holding is 0.154 and statistically significant, confirming the expectation that land is a source of income generation. Several of the Thana dummies were significant as well, suggesting regional variation in income.

The coefficient on borrowing estimates the elasticity of per-capita household consumption with respect to borrowing. This coefficient is 0.056 and significant in the OLS estimation. Inclusion of the control function raises the estimate of the borrowing coefficient to 0.177; the effect is still statistically significant below the 5% level. The increase in the effect of borrowing is due to the negative and significant coefficient on the control function. The strong significance of this coefficient (below 1%) is an indication that the estimation strategy is succeeding in capturing the endogeneity of borrowing. The negative sign is evidence that there is a negative correlation between the random error components, ε_1 and ε_2. Pitt and Khandker also find a negative correlation between the errors, and interpret the sign as an evidence that microfinance programmes are successfully targeting poorer clients.

The village characteristics specification does not identify as many predictors of borrowing as the Thana dummy specification does, but the results lead to similar conclusions. Estimates for the borrowing equation (Equation 21), using village characteristics to control for location, are presented in Table 5, where the interpretation of the estimated $\hat{\pi}$ is subject to the same normalizations discussed above. Here, only the age of the head of household is statistically significant at 5%. However, this result

Table 4. Dependent variable: log consumption.

	OLS		CF method	
Log borrowing	0.056***	(0.017)	0.177**	(0.077)
Control function			−0.979***	(0.332)
Log landholding	0.020**	(0.008)	0.154**	(0.07)
Education of head	−0.005	(0.007)	−0.001	(0.043)
Sex of head	−0.003	(0.085)	0.113	(0.171)
Age of head	−0.070	(0.045)	−0.055	(0.108)
Max ed male	0.020***	(0.006)	0.032	(0.046)
Max ed female	0.011**	(0.006)	0.020	(0.032)
No adult male present	−0.104	(0.094)	−0.008	(0.044)
No adult female present	0.642***	(0.148)	0.071	(0.778)
No spouse present	0.129**	(0.058)	0.029	(0.03)
Head's parents own land	0.016	(0.023)	0.027	(0.025)
# head's brothers own land	0.013	(0.012)	0.029	(0.025)
# head's sisters own land	0.017	(0.011)	0.034	(0.025)
Spouse's parents own land	0.027	(0.018)	0.021	(0.026)
# spouse's brothers own land	−0.006	(0.009)	−0.004	(0.026)
# spouse's sisters own land	−0.001	(0.011)	0.009	(0.026)

Standard errors in parentheses, computed by 1,000 bootstrap iterations. *, **, *** denote 10%, 5% and1% significance, respectively. The estimation sample is households for which borrowing was greater thanzero: n=813. Controls include set of Thana dummies.

Table 5. Dependent variable: log borrowing.

Education of head	0.520	(0.365)
Sex of head	−0.862	(1.03)
Age of head	1.194**	(0.547)
Max ed male	−0.492	(0.386)
Max ed female	−0.336	(0.251)
No adult male present	−0.349	(0.272)
No adult female present	−0.277	(0.197)
No spouse present	0.049	(0.255)
Head's parents own land	−0.099	(0.223)
# head's brothers own land	−0.038	(0.221)
# head's sisters own land	−0.085	(0.214)
Spouse's parents own land	−0.067	(0.234)
# spouse's brothers own land	0.041	(0.245)
# spouse's sisters own land	0.048	(0.222)
Village has primary school	−0.098	(0.251)
Village has rural health centre	0.074	(0.239)
Village has family planning centre	0.290	(0.245)
Midwife available in village	0.188	(0.252)
Village distance to bank (km)	0.090	(0.226)
Village price of rice	−0.118	(0.273)
Village price of wheat flour	−0.212	(0.297)
Village price of milk	0.134	(0.298)
Village price of hen egg	−0.024	(0.179)
Village price of potato	0.015	(0.235)
Village average male wage	0.242	(0.257)
Village average female wage	0.333	(0.396)
No village female wage	0.233	(0.379)

Standard errors in parentheses, computed by 1,000 bootstrap iterations. *, **, *** denote 10%, 5% and 1% significance, respectively. n = 1,457.

Table 6. Dependent variable: log consumption.

	OLS		CF method	
Log borrowing	0.023	(0.014)	0.212***	(0.072)
Control function			−0.951***	(0.309)
Log landholding	0.017**	(0.008)	0.126**	(0.062)
Education of head	−0.001	(0.007)	−0.037	(0.04)
Sex of head	−0.008	(0.086)	0.022	(0.154)
Age of head	−0.071	(0.045)	−0.141	(0.103)
Max ed male	0.018***	(0.007)	0.065	(0.044)
Max ed female	0.012**	(0.006)	0.055*	(0.031)
No adult male present	−0.075	(0.094)	−0.011	(0.037)
No adult female present	0.598***	(0.149)	0.064**	(0.032)
No spouse present	0.108*	(0.058)	0.023	(0.027)
Head's parents own land	0.007	(0.023)	−0.002	(0.024)
# head's brothers own land	0.010	(0.012)	0.034	(0.023)
# head's sisters own land	0.010	(0.011)	0.020	(0.023)
Spouse's parents own land	0.018	(0.018)	0.005	(0.023)
# spouse's brothers own land	−0.009	(0.01)	−0.018	(0.024)
# spouse's sisters own land	−0.015	(0.011)	−0.042*	(0.023)
village has primary school	−0.124***	(0.029)	−0.047*	(0.025)
village has rural health centre	−0.097*	(0.059)	−0.048*	(0.028)
village has family planning centre	0.049	(0.044)	0.026	(0.029)
midwife available in village	−0.082***	(0.03)	−0.042*	(0.025)
village distance to bank (km)	−0.005	(0.004)	−0.019	(0.022)
village price of rice	−0.014	(0.018)	−0.030	(0.03)
village price of wheat flour	0.041**	(0.016)	0.067**	(0.029)
village price of milk	0.001	(0.005)	−0.012	(0.03)
village price of hen egg	0.001	(0.005)	0.008	(0.024)
village price of potato	0.008	(0.009)	0.007	(0.028)
village average male wage	0.002	(0.001)	0.028	(0.027)
village average female wage	−0.002	(0.003)	−0.032	(0.043)
no village female wage	0.010	(0.057)	0.009	(0.044)

Standard errors in parentheses, computed by 1,000 bootstrap iterations. *, **, *** denote 10%, 5% and 1% significance, respectively. The estimation sample is households for which borrowing was greater than zero: n= 813.

(along with the imposed significance of log borrowing; recall that its coefficient is set to unity) still captures enough heteroscedasticity to move the coefficients in the primary estimation for consumption. Table 6 presents the estimates of the log consumption equation under the village characteristic specification. Here again, the coefficient on log borrowing is δ, the coefficient on the control function is ρ_0, and the remaining coefficients are β in Equation (27). The coefficient on borrowing rises from 0.023 to 0.212 after inclusion of the control function, an even greater increase than in the previous specification, significant at 1%. Once again, the coefficient on the control function is negative and significant, indicating a negative correlation between the error components ε_1 and ε_2. The amount of land held by a household is again found to be significant at 5%, although the elasticity is slightly smaller, at 0.126. An additional year of maximum education of a female in the household is found to increase consumption by around 6% (at a 10% significance level), while the absence of an adult female increases consumption (at 5% significance). Household consumption was lower (at 10% significance) in villages that had a primary school, a rural health centre, or a midwife available. This is perhaps due to targeting of these services or concentration of poverty closer to urban areas. A higher price of wheat flour led to higher consumption, significant at 5%.

Table 7. Heteroscedasticity indices.

	Thana specification		Village specification	
Education of head	0.276	(0.315)	−0.405	(0.271)
Sex of head	−0.076	(0.652)	−0.100	(0.626)
Age of head	0.365	(0.50)	−0.467	(0.483)
Max ed male	−0.588**	(0.292)	−0.103	(0.291)
Max ed female	−0.202	(0.213)	0.116	(0.205)
No adult male present	−0.112	(0.200)	−0.189	(0.183)
No adult female present	0.067	(0.937)	−0.025	(0.142)
No spouse present	−0.300	(0.213)	−0.081	(0.215)
Head's parents own land	0.195	(0.183)	−0.212	(0.183)
# head's brothers own land	0.159	(0.210)	0.704***	(0.212)
# head's sisters own land	0.394*	(0.220)	0.241	(0.177)
Spouse's parents own land	−0.178	(0.197)	−0.375*	(0.198)
# spouse's brothers own land	−0.009	(0.189)	0.141	(0.200)
# spouse's sisters own land	0.066	(0.195)	−0.375*	(0.197)
Village has primary school			0.072	(0.191)
Village has rural health centre			−0.423*	(0.226)
Village has family planning centre			0.181	(0.198)
Midwife available in village			−0.141	(0.205)
Village distance to bank (km)			0.025	(0.191)
Village price of rice			−0.365*	(0.213)
Village price of wheat ?our			0.314	(0.226)
Village price of milk			−0.082	(0.212)
Village price of hen egg			0.066	(0.122)
Village price of potato			−0.172	(0.175)
Village average male wage			0.209	(0.188)
Village average female wage			−0.015	(0.272)
No village female wage			0.290	(0.268)
Thana dummies	X			

Standard errors in parentheses, computed by 1,000 bootstrap iterations. *, **, *** denote 10%, 5% and 1% significance, respectively. The estimation sample is households for which borrowing was greater than zero: n= 813.

Table 7 presents the coefficient estimates for the index of the heteroscedasticity function of the consumption equation in each specification (the γ in Equations 23–27). Again, the coefficient on log borrowing has been normalized to one. These parameters have no direct interpretation, other than to note that some of them are significantly different from zero, including the variables capturing the landholding of relatives of household members. More of the coefficients are significant in the village-characteristics specification, indicating that this model may better capture the heteroscedasticity present in the consumption equation.

V. Discussion

The rapid spread of microcredit in recent years is an indication that many people believe it can be successful at combating poverty. In finding that microcredit borrowing from the flagship Grameen Bank and other similar institutions raises household consumption, the results of this article therefore confirm the beliefs of numerous microcredit practitioners and donors, which have so far been based on anecdotal evidence alone. While the scarcity of empirical evidence on this topic to date has raised doubts about the effectiveness of microcredit, the finding that borrowing has a positive and significant impact on consumption is in this sense what many have expected.

Theoretical results also predict that the impact of microcredit could be large. If the principle of diminishing returns to capital holds, microenterprises with relatively little capital should be able to earn high returns on their investments (Armendariz and Morduch). The average size of a loan disbursed by the Grameen Bank is 100 USD. At the average, then, the results above predict that an additional 100 USD in lending can be expected to increase per-capita household consumption by around 18–20%. In absolute terms, this is a small amount of consumption, given that the average household income in Bangladesh is around 600. USD Such small amounts can make a substantial difference for households that are living in extreme poverty, however.

The elasticities discussed above are larger in magnitude than those found in the previous literature, much of which finds no impact of borrowing on consumption at all. In the case of the randomized controlled trials, which look at consumption around one to three years after borrowing, the difference in results is in keeping with the model of household investment suggested by Banerjee, Karlan, and Zinman (2015). As discussed above, the benefits of microcredit borrowing might not be immediately evident, and my estimates incorporate borrowing over a longer span of time. In addition, much of the existing literature estimates the intent-to-treat effect, or the impact on a household of living in a treatment village, and suffers from low statistical power. Estimates of the effect of borrowing at the household level, in describing the expected gains from actually borrowing, can be expected to be larger and more precisely estimated.

The elasticity estimates found here are also higher than those found by Pitt and Khandker using the same data. While both studies detected positive and significant effects of borrowing, the estimates presented here are larger in magnitude and farther from the OLS estimates. This is evidence that the strategy employed here is more successful at identifying the endogeneity of borrowing. It is clear from the results that failure to appropriately control for the endogeneity of borrowing leads to severe underestimation of the impact of borrowing on consumption, and also that the restrictions imposed above on the conditional second moments of the data are sufficiently informative to identify that endogeneity.

VI. Conclusion

This article estimates the impact of borrowing from a microcredit institution in Bangladesh on per-capita household consumption. By appropriately controlling for the endogeneity of borrowing, I am able to estimate the average effect of a microcredit loan for a randomly selected household in the survey areas. By imposing an assumption that the errors in the model have a constant correlation, conditional on the exogenous variables, I am able to exploit the presence of heteroscedasticity in the model to control for the endogeneity of borrowing.

I find that microcredit loans have a positive and significant impact on consumption, with an elasticity in the range of 0.177 to 0.212. These estimates contribute to the debate over whether microcredit is reducing poverty in Bangladesh by finding that microcredit loans are succeeding in allowing households to raise their levels of consumption.

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