The Impact of Microcredit on the Poor in Bangladesh: Revisiting the Evidence

DAVID ROODMAN* & JONATHAN MORDUCH**

*Center for Global Development, Washington, DC, USA, **Financial Access Initiative, New York University, New York, USA

Online Appendix. Linear LIML is robust to skew in errors and PK estimator is not

We simulate two data-generating processes. The first complies with (1) in the main text. Credit choice, c_f and c_m , is random and uncorrelated across genders. Borrowing propensity, y_f^* and y_m^* , is 0 where credit is unavailable, and is censored from below at 0 where credit is available. All errors are standard normal:

$$\epsilon_f, \epsilon_m, \eta, c_f^*, c_m^* \sim \operatorname{iid} \mathcal{N}(0, 1)$$

$$\epsilon_o = (\epsilon_f + \epsilon_m + \eta) / \sqrt{3}$$

$$c_f = \mathbf{1} \left\{ c_f^* > 0 \right\}$$

$$c_m = \mathbf{1} \{ c_m^* > 0 \}$$

$$y_f^* = c_f \epsilon_f$$

$$y_m^* = c_m \epsilon_m$$

$$y_f = \mathbf{1} \left\{ y_f^* > 0 \right\} \cdot y_f^*$$

$$y_m = \mathbf{1} \left\{ y_m^* > 0 \right\} \cdot y_m^*$$

$$y_o = \mathbf{1} \cdot y_f + 1 \cdot y_m + \epsilon_o$$

The parameters of interest are the coefficients in the last line.

The second data-generating process differs only in transforming ϵ_o after the second line above to have a $\chi^2(15)$ distribution that is shifted and scaled to keep the mean and variance at 0 and 1. The transformation is $(\Xi_{15}^{-1}(\Phi(\cdot)) - 15)/\sqrt{2 \times 15}$, where $\Xi_{15}^{-1}(\cdot)$ is the inverse c.d.f. of the $\chi^2(15)$ distribution and $\Phi(\cdot)$ is the standard normal c.d.f. This gives ϵ_o a skew of $\sqrt{8/15} \approx 0.73$, close to the value reported in Table 3 for the PK replication.

We apply linear LIML and PK's estimator to 100 simulated data sets of each variety. The linear LIML regressions instrument y_f and y_m with c_f and c_m . The results confirm that, contrary to the criticism in PK (2012) relating to weak instruments, linear LIML is consistent; and that the PK estimator is more efficient when its assumptions are satisfied (left half of Table A-1). But when the

normality assumption is violated (right half), the PK estimator is inconsistent. This again contradicts PK (2012)—or at least answers their argument that no one has proved that their estimator is inconsistent.

Table A-1. Mean coefficient estimates, 100 simulations, with and without skew in second-stage error

| | Normal error | | Skewed error | |
|--------------|--------------|-----------------|--------------|---------|
| | y_f | \mathcal{Y}_m | y_f | y_m |
| PK estimator | 0.996 | 0.998 | 1.112 | 1.124 |
| | (0.025) | (0.025) | (0.030) | (0.031) |
| Linear LIML | 0.996 | 0.990 | 0.990 | 1.008 |
| | (0.046) | (0.054) | (0.050) | (0.054) |

True coefficients are 1.0. Standard deviations in parentheses.