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MITIGATING LOAN REPAYMENT TROUBLES DURING MICROFINANCE EXPANSION: EVIDENCE FROM A LARGE PANEL

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Using linear panel methods, this article tests whether the surge in microfinance lending during the boom years of 2004-2008 hurt loan repayment rates. Surprisingly, we find evidence that loan delinquency is inversely related to microfinance growth. This result is contrary to the long-standing view that fast microfinance expansion leads to increased loan delinquency. This suggests the existence of a larger pool of high quality borrowers that may have not yet been tapped in new markets. This finding is robust across estimation methods and even after controlling for cross-sectional and temporal dependencies.

Keywords: Microfinance, Microfinance Institutions, Loan Delinquency, Panel Estimation
JEL Classification: G21; G32

1. INTRODUCTION

One of the core objectives of microfinance institutions (MFIs) is the provision of banking/financial services to non-traditional customers known as poor and low-income households or businesses. A significant challenge facing these institutions is the struggle for financial self-sufficiency. This means controlling most of the risks in the loan portfolio through adequate loan collection and timely loan repayments. Doing so, provides for further extension of funds to other borrowers, resulting in further outreach and development (Crabb and Keller, 2006).

Examining this challenge in the presence of uncontrolled growth is of importance, since fast microfinance growth could pose substantial strain on MFIs' mission, making it harder for them to operate sustainably in such an unconventional market structure. In addition, the 2004-2008 surge in microfinance provides a great opportunity to test this hypothesis.

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There is a paucity of empirical work on the effects of the unprecedented rapid microfinance expansion that occurred between 2004 and 2008. Practitioners have speculated that this high growth phase in microfinance activities has led to increased loan delinquency. According to Gonzalez (2009), the increase in the number of borrowers during the expansion averaged 21 percent per year while loan portfolio jumped by a staggering 34 percent per year on average.

Chen et al. (2010) and Stephens (2009) examine some of the emerging economies qualified as "high growth" markets and show that in 2008, these markets[1] experienced devastating loan delinquency rates. These studies feed into the narrative that aggressive growth in microfinance lending may pose higher credit risk to MFIs as loan recovery efforts become more challenging. Chen et al. (2010) identified key contributing factors to poor loan repayment rates among which high microfinance growth is mentioned. However, they present no empirical evidence.

In this paper, we use a new and improved proprietary comprehensive dataset that includes a large cross-section of MFIs to estimate the effect of rapid microfinance expansion on loan delinquency. The use of such a comprehensive data mitigates that kind of measurement error that plague many microfinance studies (missing data) and allows us to estimate linear panel models. Given that the effects of microfinance expansion may not be visible during the boom years (2004-2008), we extend our dataset from 2003 to 2013[2] to include post-boom years. For proper identification of the effect of microfinance expansion on loan delinquency, we control for aspects of microfinance (micro) and beyond-microfinance (macro) design.

2. DETERMINANTS OF LOAN REPAYMENT

Loan repayment is the most revealing of the five[3] performance areas of a MFI (Rosenberg, 2009). So, the ability to collect loans is critical to the success of MFIs. We use the loan loss rate to proxy loan repayment.

$$Loan\ loss\ rate = \frac{Adjusted\ Write\text{-}offs, net\ of\ recoveries}{Average\ Gross\ Loan\ Portfolio}. \quad (1)$$

The loss loan rate measures how well a MFI collects its loans and our presumption is that higher values of loan loss rate are associated with lower repayment rates.

To measure the impact of microfinance growth on loan delinquency, it is important

[1] These microfinance markets are: Nicaragua, Morocco, Bosnia and Herzegovina (BiH), and Pakistan.

[2] The most recently available data is for year 2013. We also estimated our model during the boom years only (not presented in this paper) and found qualitatively similar results.

[3] The four other performance areas are: 1) outreach: breadth (number of clients served), 2) outreach: depth (client poverty level), 3) financial sustainability (profitability) and 4) efficiency.

to control for factors that may explain changes in loan repayment. The choice of control variables is motivated by the literature. We hypothesize that loan repayment is influenced by the growth of lending,[4] the percentage of female borrowers,[5] other (micro) institutional factors[6] such the personnel allocation ratio (percent of staff devoted to credit control), the quality of prudential regulation, the quality of technical assistance, operational self-sufficiency, financial intermediation and credit risk (portfolio at risk more than 30 days) and macroeconomic variables[7] (GNI per capita growth rate and inflation) that may affect the ability of the MFI to recover loans.

Following the Microfinance Information Exchange (MIX) Market definition, operational self-sufficiency is calculated as follows:

$$OSS = \frac{Financial\ Revenue}{Financial\ Expense + Impairment\ Loss + Operating\ Expense}. \quad (2)$$

It is a ratio which indicates whether enough revenue has been earned to cover the MFI's total costs—operating expenses, loan loss provisions and financial costs. It measures how sustainable the lending operations are.

We use Portfolio at Risk (PAR) > 30 days to measure the credit risk of an MFI. PAR > 30 days is defined as follows:

$$PAR > 30\ Days = \frac{Outstatnding\ balance, loans\ overdue > 30\ Days}{Adjusted\ Gross\ Loan\ Portfolio\ during\ period}. \quad (3)$$

3. EMPIRICAL MODEL AND DATA

3.1. Standard Linear Panel Model

We consider the following general panel data model:

$$y_{it} = X'_{it}\theta + \mu_i + \varepsilon_{it}, \qquad i = 1, \dots, N,\ t = 1, \dots, T \quad (4)$$

where y_{it} is the dependent variable—loan loss rate—which we use to proxy loan repayment, X_{it} is the vector of control variables of MFI i at time t, the μ_i's represent the MFI-specific fixed effects and ε_{it} denotes the remainder disturbance.

3.2. Cross-sectional and Temporal Dependencies

4 The growth rate of lending is calculated by measuring the year on year increase in active borrowers. See Gonzalez (2010) and Ghatak and Guinnane (1999).

5 Ledgerwood (1998) and Malik et al. (2013) among others

6 Yimga (2015)

7 Woolley (2008) Weele and Markowich (2001)

Microeconomic data are likely to exhibit all sorts of cross-sectional and temporal dependencies because the units are not randomly sampled[8] and the MFIs in the MIX Market database we use, self-report. These dependencies might intensify especially during period of fast growth in microfinance activities.

Erroneously ignoring possible correlation of regression disturbances over time and between MFIs (mostly those located in the same country) can lead to biased statistical inference. To ensure validity of the statistical results, we follow recent studies' methodology which include a regression on panel data with adjustment of standard errors of the coefficient estimates for possible dependence in the residuals.

We implement Driscoll and Kraay's (1998) covariance matrix estimator for use with pooled Ordinary Least Squares (OLS) estimation and fixed effects (within) regression. Apart from being heteroscedasticity consistent, these standard error estimates are robust to very general forms of cross-sectional and temporal dependence. However, to accommodate the unbalancedness of our panel dataset, we use the adjustment to Driscoll and Kraay's (1998) covariance matrix estimator by Hoechle's (2007) described in the Appendix.

3.3. Data

The data used in this study is collected from the MIX Market database. The consequent data used after cleaning is an unbalanced panel data of 998 MFIs in 101 countries across 5 regions:[9] Africa, East Asia and the Pacific, Eastern Europe and Central Asia, Latin America and The Caribbean, Middle East and North Africa, South Asia, over the period 2003-2013.

In Table 1, we report cross-sectional averages for all variables used for estimation. On average, MFIs devote more that 50 percent of their staff to lending activities and post-disbursal monitoring and each loan officer oversees a little over 300 borrowers. More than 60 percent of MFIs in our sample are regulated while women constitute more than 65 percent of microfinance clientele.

The correlation matrix of the variables used for estimation is reported in Table 2 with significant correlation coefficients in bold. Column 1 of Table 2 shows how the dependent variable—loan loss rate—correlates with the control variables. The signs of the correlation coefficients in column 1 are consistent with our expectations. The other correlations in Table 2 and calculated variance inflation factors (not reported) suggest that multicollinearity is not a problem in our dataset.

[8] Hoechle (2007)

[9] The MIX Market collects microfinance information all around the globe and this information is collected across 5 regions predetermined by the MIX Market.

Table 1. Data Summary Statistics (cross-section averages)

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Loan Delinquency (Dependent Variable)											
Loan Loss Rate	0.012	0.051	0.025	0.009	0.012	0.013	0.018	0.018	0.017	0.019	0.056
Microfinance growth											
Growth in number of active borrowers	0.288	0.256	0.307	0.324	0.307	0.195	0.139	0.151	0.102	0.081	2.07E-04
Personnel Allocation Ratio											
% Staff devoted to Credit Control	56.2	56.1	56.9	54.7	54.9	46.8	46.5	45.4	45.1	47.9	55.8
Prudential Regulation											
Regulated (Dummy = 1 if MFI is regulated	0.657	0.610	0.603	0.601	0.590	0.595	0.602	0.609	0.611	0.654	0.765
Quality of Technical Assistance											
Borrowers per loan officer	275	260	284	282	273	341	354	340	350	507	184
Operational Self-sufficiency (OSS)											
Financial Revenue / (Financial Expense + Impairment Loss + Operating Expense)											
OSS	1.156	1.185	1.164	1.160	1.196	1.216	1.128	1.173	1.152	1.180	1.012
Financial Intermediation (FI)											
Equals 1 if Voluntary savings >20% of total assets	0.279	0.257	0.313	0.333	0.337	0.354	0.356	0.378	0.406	0.443	N/A
Gender											
% Female Borrowers	68.1	67.9	69.7	68.4	67.5	65.4	65.5	66.9	68.2	61.7	52
Credit Risk											
Portfolio at Risk (PAR) >30 days	0.064	0.053	0.046	0.050	0.045	0.056	0.068	0.073	0.068	0.063	0.057
Macroeconomic Indicators											
GNI per Capita (U.S. Dollar)	1262.86	1449.57	1775.84	1968.19	2432.84	2805.12	2862.67	3254.75	3459.09	2858.25	3238.76
Inflation (%)	5.98	6.31	6.64	6.48	6.84	11.97	5.66	6.36	7.72	8.11	7.61

Source: MIX Market

Table 2. Correlations

	Variables	1	2	3	4	5	6	7	8	9	10	11
1	Loan Loss Rate	1										
2	Growth of lending	**-0.109**	1									
3	Personnel Allocation Ratio	-0.018	**0.122**	1								
4	Borrowers per loan officer	**-0.055**	0.025	**-0.231**	1							
5	Prudential Regulation	-0.012	**0.037**	**-0.031**	-0.019	1						
6	Operational Self-sufficiency	-0.026	0.006	0.004	**0.079**	-0.004	1					
7	Financial Intermediation	**-0.067**	**-0.066**	**-0.149**	**0.064**	**0.267**	-0.014	1				
8	% Female Borrowers	-0.005	**0.059**	**0.317**	**0.269**	**-0.111**	**-0.053**	**-0.046**	1			
9	Portfolio at Risk (PAR) >30 days	**0.162**	**-0.154**	**-0.091**	0.023	0.006	**-0.093**	**0.061**	**-0.089**	1		
10	GNI per Capita (growth rate)	**-0.028**	**0.114**	0.004	**-0.047**	**0.071**	**0.056**	-0.019	**-0.062**	**-0.071**	1	
11	Inflation	-0.006	0.009	0.023	-0.006	**0.034**	-0.006	-0.017	**0.049**	-0.004	**0.157**	1

Note: Correlations in bold are significant at 5% level of significance.

4. ESTIMATION RESULTS

The estimation results in Table 3 appear to be consistent with our expectations for most variables. The coefficient for microfinance expansion - our variable of interest - is always highly significant and negative suggesting that more growth reduces loan delinquency. This result is contrary to the long-held belief that fast microfinance growth increases default risk. This is suggestive there is a huge unmet demand for microcredit in terms of credit worthy clients that have not yet been tapped by MFIs (Yimga, 2015).

Table 3. Linear Panel Estimation Controlling for Cross-sectional and Temporal Dependence. Determinants of Loan Repayment-Dependent variable is Loan Loss Rate

	POLS		FE	
	(1)	(2)	(3)	(4)
Microfinance Growth				
Growth of lending	-0.0108**	-0.0105**	-0.0124***	-0.0120***
	(0.0035)	(0.0036)	(0.0022)	(0.0021)
Personnel Allocation Ratio				
% Staff devoted to Credit Control	-0.0128***	-0.0135***	-0.0320***	-0.0338***
	(0.0037)	(0.0028)	(0.0083)	(0.0095)
Quality of Technical Assistance				
ln (Borrowers per loan officer)	-0.0044*	-0.0048**	-0.0099**	-0.0107**
	(0.0022)	(0.0019)	(0.0039)	(0.0037)
Prudential Regulation				
Regulated (Dummy = 1 if MFI is regulated)	-0.0029	-0.0014		
	(0.0016)	(0.0017)		
Operational Self-sufficiency (OSS)				
Financial Revenue / (Financial Expense + Impairment Loss + Operating Expense)				
OSS	-0.0054**	-0.0051*	-0.0031	-0.0027
	(0.0024)	(0.0023)	(0.0017)	(0.0015)
Financial Intermediation (FI)				
Equals 1 if Voluntary savings >20% of total assets	-0.0060*	-0.0067**	-0.0017	-0.0028
	(0.0028)	(0.0027)	(0.0040)	(0.0045)
Gender				
% Female Borrowers	0.0047	0.005	0.0166	0.019
	(0.0041)	(0.0042)	(0.0092)	(0.0111)
Credit Risk				
Portfolio at Risk (PAR) >30 days	0.0685***	0.0652***	0.0494***	0.0459***
	(0.0090)	(0.0080)	(0.0074)	(0.0071)
Macroeconomic Indicators				
GNI per Capita (growth rate)		-0.0359***		-0.0302***
		(0.0079)		(0.0028)
Inflation		-0.0004*		-0.0005**
		(0.0002)		(0.0002)
Constant	0.0507***	0.0591***	0.0782***	0.0884***
	(0.0145)	(0.0130)	(0.0207)	(0.0203)
No. of Obs.	4057	3926	4092	3960

Note: Shown are pooled OLS (POLS) and FE (within) linear panel regressions. Driscoll and Kraay (1998) standard errors for the slope coefficients are in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1

Most control variables have the expected sign and are statistically significant at conventional levels of significance. The coefficient estimate on personnel allocation ratio suggests that the more staff an MFI devotes to credit monitoring the more due diligence and post-disbursal monitoring which in turn results in lower loan delinquency.

The indicator variable prudential regulation has the expected sign, however, is not statistically significant, suggesting that overall, unregulated MFIs do not have consistently lower loan delinquency rates than regulated ones.

MFIs that are operationally self-sufficient have lower loan delinquency rates and MFIs with higher ability to coordinate and channel funds from savers to borrowers have consistently lower loan delinquency rates compared to their counterparts with lower intermediation ability.

Portfolio at Risk (PAR)>30 days indicate that as the outstanding balance in loans (overdue more than 30 days) rises, the potential for future loan losses also rises. Overall, we find no evidence that lending to women reduces the loan loss rate.

Table 3 also shows that these results are robust to the inclusion of macroeconomic factors even after controlling for cross-sectional and temporal dependencies.[10] This significance of macroeconomic indicators such as GNI per capita and inflation, which are beyond microfinance design-therefore uncontrollable at the institutional level, have some predictive power on loan repayment.

5. CONCLUSION

This study uses a large cross-section of MFIs over the period 2003-2013 to test whether the unprecedented growth surge of microfinance between 2004 and 2008 resulted in increased loan delinquency. The results identify key factors that explain loan delinquency, including (micro) institutional and macroeconomic factors. Most importantly though, the growth in lending-our variable of interest, long thought to be a major factor for increased loan delinquency, is inversely related to loan delinquency. This finding is suggestive of the fact that overall, the growth surge between 2004 and 2008 did not harm repayment rates and that there is vast pool of credit worthy borrowers in new markets that MFIs are still yet to serve.

[10] We also estimated (not reported in this paper) between, random effects generalized least squares (RE-GLS) and random effects maximum likelihood estimation (RE-MLE) linear panel regressions. The results are qualitatively similar to those in Table 3. These results are available upon request.

Appendix

A1. Cross-sectional and temporal dependencies for pooled OLS estimation

Following Hoechle (2007), we start by considering the linear regression model

$$y_{it} = \boldsymbol{x}'_{it}\theta + \varepsilon_{it}, \qquad i = 1, \dots, N;\ t = 1, \dots, T \tag{5}$$

where the dependent variable y_{it} is a scalar, $\boldsymbol{x}_{it}$ is a $(K+1) \times 1$ vector of independent variables whose first element is 1, and θ is a $(K+1) \times 1$ vector of unknown coefficients. i denotes the cross-sectional units (MFIs) and t denotes time. We stack all observations as follows:

$$\boldsymbol{y} = [y_{1t_{11}} \dots y_{1T_1}\ y_{2t_{21}} \dots y_{NT_N}]' \text{ and } \boldsymbol{X} = [x_{1t_{11}} \dots x_{1T_1}\ x_{2t_{21}} \dots x_{NT_N}]'.$$

This formula allows for unbalanced panel and it is assumed that the regressors $\boldsymbol{x}_{it}$ are uncorrelated with the scalar disturbance term. θ can consistently be estimated by OLS regression, which yields

$$\hat{\theta} = (\boldsymbol{X}'\boldsymbol{X})^{-1}\boldsymbol{X}'\boldsymbol{y}.$$

Driscoll and Kraay standard errors for the coefficient estimates are then obtained as the square roots of the diagonal elements of the asymptotic (robust) covariance matrix,

$$V(\hat{\theta}) = (\boldsymbol{X}'\boldsymbol{X})^{-1}\widehat{\boldsymbol{S}}_T\boldsymbol{X}'\boldsymbol{y},$$

where $\widehat{\boldsymbol{S}}_T$ is defined as in Newey and West (1987):

$$\widehat{\boldsymbol{S}}_T = \widehat{\boldsymbol{\Omega}}_0 + \boldsymbol{\Sigma}_{j=1}^{m(T)} w(j,m)[\widehat{\boldsymbol{\Omega}} + \widehat{\boldsymbol{\Omega}}'_j]. \tag{6}$$

In equation (6), $m(T)$ denotes the lag length up to which the residuals may be autocorrelated and the modified Bartlett weights,

$$w(j,m) = 1 - j/\{m(T) + 1\},$$

ensure positive semidefiniteness of $\widehat{\boldsymbol{S}}_T$ and smooth the sample autocovariance function such that higher-order lags receive less weight. The $(K+1) \times (K+1)$ matrix Ω_j is defined as

$$\widehat{\boldsymbol{\Omega}}_j = \boldsymbol{\Sigma}_{t=j+1}^{T}\mathbf{h}_t(\hat{\theta})\mathbf{h}_{t-j}(\hat{\theta})' \text{ and } \mathbf{h}_t(\hat{\theta}) = \boldsymbol{\Sigma}_{t=1}^{N(t)}\mathbf{h}_{it}(\hat{\theta}). \tag{7}$$

The contribution of Hoechle (2007) is made in equation (7), where the sum of the individual time t moment conditions $h_{t-j}(\hat{\theta})$ runs from 1 to $N(t)$, where N is allowed to vary with t. This small adjustment to Driscoll and Kraay's (1998) original estimator suffices to make their estimator accommodate unbalanced panels.

Therefore, the POLS estimation using the covariance matrix with the approach described above yields standard errors that are robust to general forms of cross-sectional and temporal dependence.

A2. Accounting for cross-sectional and temporal dependence for Fixed-effects estimation

Hoechle (2007) shows that the corresponding FE estimator is implemented in two steps.

First, all model variables $z_{it} \in \{y_{it}, x_{it}\}$ are within-transformed as follows

$$\tilde{z}_{it} = z_{it} - \bar{z}_i - \bar{\bar{z}}, \text{ where } \bar{z}_i = T_i^{-1}\Sigma_{t=t_{i1}}^{T_i} z_{it} \text{ and } \bar{\bar{z}} = (\Sigma T_i)^{-1}\Sigma_i\Sigma_t z_{it},$$

since it can be seen that the within-estimator corresponds to the OLS estimator of

$$\tilde{y}_{it} = \tilde{x}'_{it}\theta + \tilde{\varepsilon}_{it}. \tag{8}$$

In the second step, the transformed regression model in equation (8) is estimated using pooled OLS estimation with Driscoll-Kraay standard errors. We present the results with cross-sectional and temporal dependence consistent estimates in Table 3.

REFERENCES

Chen, G., S. Rasmussen, and X. Reille (2010), “Growth and Vulnerabilities in Microfinance,” *Focus Note*, 61, 1-21.

Crabb, P.R., and T. Keller (2006), “A Test of Portfolio Risk in Microfinance Institutions,” *Faith and Economics*, 47(48), 25-39.

Driscoll, J. C., and A.C. Kraay (1998), “Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data,” *Review of Economics and Statistics*, 80(4), 549-560.

Ghatak, M., and T.W. Guinnane (1999), “The Economics of Lending with Joint Liability: Theory and Practice,” *Journal of Development Economics*, 60(1), 195-228.

Gonzalez, A. (2009), *Microfinance at a Glance 2008*, Washington DC: Microfinance

Information Exchange.
Gonzalez, A. (2010), "Is Microfinance Growing Too Fast?" *MIX Data Brief*, 5, 15.
Hoechle, D. (2007), "Robust Standard Errors for Panel Regressions with Cross-sectional Dependence," *Stata Journal*, 7(3), 281-312.
Ledgerwood, J. (1998), *Microfinance Handbook: An Institutional and Financial Perspective*, Washington DC: World Bank.
Malik, K. (2013), *Human Development Report 2013*, New York: United Nations Development Programme.
Newey, W.K., and K.D. West (1987), "A Simple, Positive Semi-definite, Heteroscedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica*, 55(3), 703-708.
Rosenberg, R. (2009), *Measuring Results of Microfinance Institutions: Minimum Indicators that Donors and Investors should Track-a Technical Guide*, Washington DC: CGAP.
Stephens, B. (2009), "*MFI Benchmark Analysis: Operating Efficiency: Victim to the Crisis?*" Micro Banking Bulletin, 19, 39-44.
Weele, K. and P. Markowich (2001), "Managing High and Hyperinflation in Microfinance: Opportunity International's Experience in Bulgaria and Russia," USAID-Microent- erprise Best Practices (MBP) Project, available at: https:// www.microfinancegateway.org/library/managing-high-and-hyper-inflation-microfin ance-opportunity-internationals-experience.
Woolley, J.T. (2008), "*Microfinance Performance and Domestic GDP Growth: Testing the Resiliency of Microfinance Institutions to Economic Change*," Stanford Journal of Microfinance, 1(1), 17, available at: http://ojs.stanford.edu/ojs/index.php/sjm/article /view/507/355
Yimga, J.O. (2015), "The impact of high microfinance growth on loan portfolio. Journal of International Development," Journal of International Development, 28, 697-714.

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